smart cities

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Review

A Bibliometric Analysis of Research on the Convergence of Artificial Intelligence and Blockchain in Smart Cities

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Abstract: Smart cities aim to enhance the quality of life for citizens by integrating information technology in various aspects of daily life. This paper focuses on recent innovations in the integration of two prominent technologies, artificial intelligence (AI) and blockchain, to manage complex interactions between smart connected devices, individuals, government agencies, and the private sector. By conducting a systematic scientometric analysis and visualization of 505 articles published between 2017 and 2023, we uncover the social, conceptual, and intellectual structures of the literature in this field through co-authorship, co-word, and co-citation networks. Our analysis identifies key insights, research hotspots, specialties, and emerging trends by examining important nodes in the bibliometric networks. The findings of this study can be of interest to both academics and practitioners working in the fields of AI, blockchain, and smart cities.

Keywords: 5G network; federated deep learning; Internet of things (IoT); reinforcement learning; smart contract; systematic review

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1. Introduction

Modern cities worldwide are undergoing significant changes to promote a clean, sustainable, and secure environment by implementing smart infrastructures, intelligent services, and greater accessibility for residents, especially vulnerable groups [1]. The primary objective of these smart cities is to improve daily life in urban areas by integrating information technologies into routine activities [2]. Meeting critical needs, such as e-government, urban mobility, healthcare, water management, waste management, clean energy production and consumption, energy saving, payment, housing, safety, and accessibility, requires the adoption of new digital technologies. Two emerging technologies that can facilitate the management of these complex interactions between citizens, government agencies, and the private sector are artificial intelligence (AI) and blockchain. AI enables computing machines to learn, infer, and adapt based on data [3], while blockchain is an immutable, public digital ledger distributed among networked peers [4]. With blockchain, any transaction recorded must be cryptographically signed and verified by all nodes for consensus [5].

In such an ecosystem, a vast amount of data is collected from sensors, networked devices, individuals, organizations, and other sources. To provide a sustainable environment, this data must be properly processed and analyzed. The integration of AI technology into smart city environments aims to improve decision-making skills and enhance the delivery of public and urban services [2]. However, implementing smart ecosystems poses significant security and privacy challenges [1,6,7]. Blockchain has the ability to overcome many of these challenges. The data within a block is virtually impossible to alter due to cryptographic hashing [7] and the linkage between subsequent blocks, which requires generating hashes for all those blocks. A consensus mechanism is another factor that prevents changes in blocks as the generated/changed blocks must be accepted by all network nodes.

Hence, blockchain securely manages various entities such as smart contracts, smart assets, digital identities, etc., in a distributed network. The combination of blockchain and AI in the context of smart cities addresses a range of issues, including authentication, digital signature, validation, smart contracts, decentralization, secure sharing, and explainable AI.

Researchers have conducted surveys in particular fields of smart cities regarding the convergence of AI and blockchain. The study by Singh et al. [8] on Internet of things (IoT) networks is a breakthrough in this field, aiming to transform sustainable ecosystems using a new network architecture in smart cities. The researchers provide a comprehensive overview of security issues, problems, and key factors affecting the convergence of blockchain and AI in the formation of a sustainable smart society based on the IoT network. Kiruthika and Ponnuswamy [2] see the primary goal of combining AI, blockchain, and IoT in smart cities as utilizing a technical solution to process and analyze a large amount of data collected from people, devices, and other IoT sources through AI methods. They suggest that the second goal of this fusion is to ensure data security when processed by AI and to manage various entities such as smart contracts, smart assets, and the digital identity of people using blockchain. Gupta et al. [9], on the other hand, conduct similar research on the fusion of AI, blockchain, and 5G technologies, not exactly aimed at using them in smart cities but exploring the possibility of applying the results.

In order to develop innovative solutions, several scholars have proposed integrating AI and blockchain in the context of smart cities. Sharma et al. [7] present a blockchain-based IoT framework that integrates AI and blockchain for IoT applications. They evaluate the performance of their proposed architecture using qualitative and quantitative measurements. Rajawat et al. [10] propose a framework based on AI and blockchain to improve the security of biomedical and healthcare data, which are subsets of smart cities. The integration of blockchain and AI for IoT applications enables the use of AI in digital signature, authentication, distributed ledger, smart contracts, and data security within a decentralized network [7], thereby addressing critical challenges in the context of smart cities.

In an analysis of the concurrent application of AI and blockchain in the context of smart cities, Badidi [1] conducts a systematic review of 150 articles to explore the transformative potential of edge AI and blockchain. The author addresses the current challenges faced by smart cities and examines the multiple applications of edge AI and blockchain in the fields of smart mobility and smart energy. This includes relevant research efforts related to vehicle detection, counting, speed identification, traffic congestion, trustworthy communications, trading between vehicles, and smart energy trading. In a similar vein, Singh et al. [11] review the extensive literature on safety issues and challenges that affect the use of blockchain in the development of sustainable smart societies. They focus on solutions to blockchain security issues and important concepts for developing smart transportation techniques based on AI and blockchain.

To the best of our knowledge, there are few bibliometric studies on the convergence of AI and blockchain in the context of smart cities. These studies provide limited insight into the evolution of this field and only cover a few applied areas of this convergence. In light of this, our research aims to identify the potential and areas of interest for the integration of AI and blockchain in smart cities and to provide a state-of-the-art overview of these two technologies using scientometric visualization. The remainder of this paper is structured as follows: Section 2 outlines our data retrieval strategy and process, discusses our research questions, and describes our methodology. Section 3 presents descriptive statistics and a geographic analysis of the literature on the integration of AI and blockchain in smart cities, as well as the results of our social structure, conceptual structure, and intellectual structure analyses. In Section 4, we discuss the significance of our results by comparing them with those of other studies in this field. Finally, Section 5 provides our concluding remarks.

2. Materials and Methods

In recent years, there has been a growing interest among scholars in exploring the potential applications of AI and blockchain for smart cities. However, to gain a better understanding of the evolution of research in this area and identify potential future research directions and opportunities, it is necessary to investigate the history of research through scientometric analysis of high-quality scientific literature. Such an analysis can help identify the distribution of studies on the subject and shed light on promising avenues for future research. The framework SALSA (Search, Appraisal, Synthesis and Analysis) [12] is the primary methodology used in this study to conduct a systematic review of relevant research. Systematic reviews are essential in reducing the likelihood of bias and ensuring that a comprehensive body of knowledge on the chosen subject is accurately identified [13]. By following a systematic approach, this study can evaluate all available research related to a set of research questions.

This study outlines a systematic process to define the research questions, identify a suitable database, determine the search terms, select analytical software, extract relevant data, and analyze the findings. These steps are illustrated in Figure 1 and elaborated further in the subsequent paragraphs.

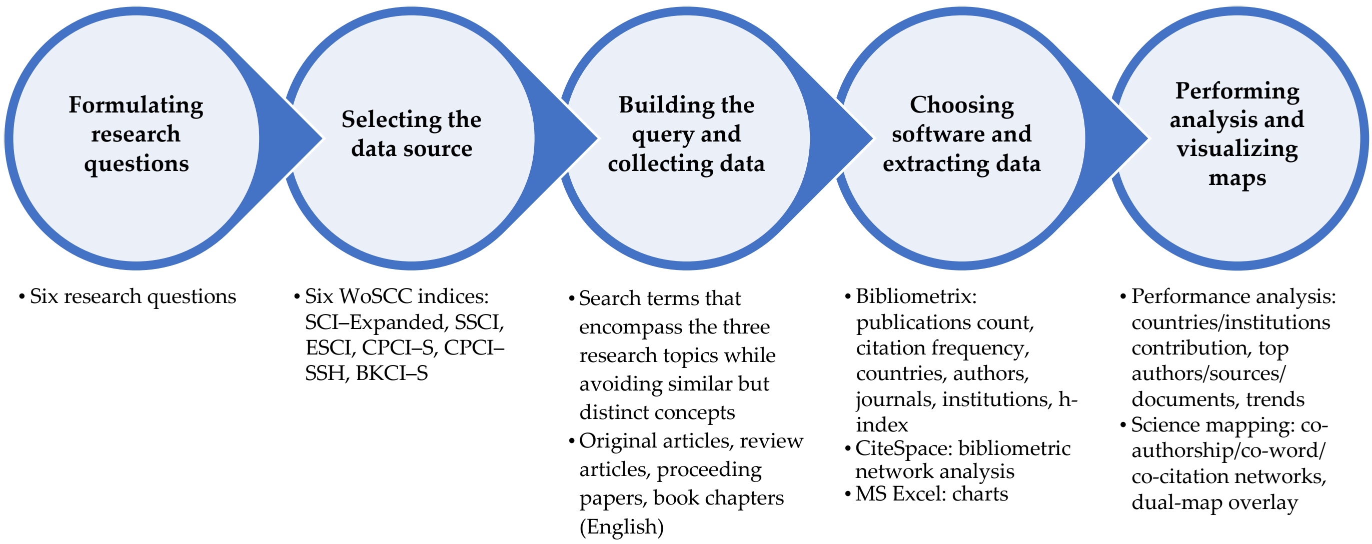

Figure 1. Methodological scheme for the research.

2.1. Research Questions

To ensure a comprehensive and focused analysis, a bibliometric review should be guided by clear research questions. Therefore, this paper is organized around the following research questions, aimed at providing an overview of the convergence of AI and blockchain in smart cities:

1. What is the current state of research on the fusion of AI–blockchain in smart cities?
2. What are the most influential and productive publications in this field?
3. Who are the main contributors and collaborators in this research area?
4. What are the main themes and concepts related to this integration?
5. What are the geographic distribution and collaborative networks of researchers working in this field?
6. What are the potential future research directions and opportunities in this area?

2.2. Data Source

The Web of Science Core Collection (WoSCC) is the primary source of data for this study, as it covers a vast amount of high-quality scientific literature across a range of disciplines. It is widely regarded as one of the most appropriate databases for bibliometric analysis of scientific publications [14]. Out of the ten indices available in the WoSCC, which includes information from a vast number of scholarly journals, books, book series, conferences, and more, three indices are selected as the primary data sources: Science Citation Index Expanded (SCI–Expanded), Social Sciences Citation Index (SSCI), and Emerging

Sources Citation Index (ESCI). To ensure comprehensive coverage of the research topic and to reduce publication bias, three secondary data sources are also used, including Conference Proceedings Citation Index—Science (CPCI–S), Conference Proceedings Citation Index—Social Science & Humanities (CPCI–SSH), and Book Citation Index—Science (BKCI–S). This approach allows for a more complete representation of the literature, encompassing journal articles, conference papers, and book chapters.

2.3. Data Collection

To avoid any bias caused by database updates, a separate search was conducted on 21 December 2022 to retrieve the literature. The query string, which is provided in Appendix B, contains the principal terms 'artificial intelligence,' 'blockchain,' and 'smart city,' as well as their relevant keywords. To identify related keywords for each of these three domains, we examine the scope and subjects covered by the most frequently cited journals in each area, based on their impact factor or CiteScore.

The most cited journals in the AI and machine learning field, i.e., *The IEEE Transactions on Pattern Analysis and Machine Intelligence*, *Foundations and Trends® in Machine Learning*, and *The IEEE Transactions on Cognitive Communications and Networking*, offer related keywords that help scope out this area. Meanwhile, *Frontiers in Blockchain*, *The Journal of the British Blockchain Association*, and *Ledger* were consulted to identify blockchain-related keywords. To extract the keywords related to smart cities, the journals of Smart Cities, IET Smart Cities, and City and Environment Interactions were analyzed.

Only original articles, review articles, proceeding papers, and book chapters are considered in this study. We retrieve a list of all relevant papers from the WoSCC, which includes titles, keywords, author information, abstracts, and references, and save them in plain text format. These data are then analyzed using CiteSpace [15] and Bibliometrix [16].

2.4. Data Extraction

The selected documents are imported into CiteSpace and Bibliometrix for further data analysis. The extracted data includes general information such as annual number of publications, citation frequency, original countries, authors, journals, and institutions. Journal impact factor is obtained from the Journal Citation Reports (JCR) 2021 (available at: http://thomsonreuters.com/journal-citation-reports, accessed on 25 December 2022), which is widely used for rating a journal's performance in its field. The h-index is another important indicator used to assess the scientific production and academic impact of researchers, countries, institutions, or journals [17,18]. The processed information extracted from the two software tools includes necessary data for drawing diagrams and describing networks and their clusters. This information includes the number of publications for both authors and sources, their average annual citation count, the h-index calculated internally for each, the number of keywords, the results of the cluster naming algorithms, and indicators for assessing the adequacy and novelty of the topic clusters.

2.5. Data Visualization and Analysis

The Bibliometrix R-package is utilized for conducting descriptive statistical analysis of the extracted data. Charts are drawn using MS Excel. Furthermore, scientific literature visualization networks are constructed using CiteSpace. These networks consist of researchers, journals, and research institutions, as well as keywords, titles, and abstracts as network nodes. These nodes are linked through co-authorship, co-citation, and co-occurrence analysis. Co-authorship analysis determines the similarity relationships between items based on the number of co-authored documents, while co-citation and co-occurrence analyses illustrate the relationship between items based on the number of times they are cited together and the number of studies where they appear together, respectively [19].

3. Results

This section presents the findings obtained from the data visualization of the total sample of 505 publications selected based on the search strategy explained in Section 2.3. The primary results of this study include bibliometric maps of co-authorship among authors and institutions, co-citation among authors, journals, and references, and co-occurrence of keyword and terms. Additionally, a dual-map overlay of journals is created to provide a comprehensive view of the interconnections among the identified journals [20]. To better understand the evolution of this field over time, descriptive statistics are presented in tabular and graphical formats.

3.1. Demographic Perspective of the Study Area

3.1.1. Basic Summary of the Sampled Publications

The forthcoming sections will present the result of a bibliometric analysis conducted on a dataset of 505 publications, comprising of 335 journal articles (66.33%), 93 conference papers (18.42%), 75 review articles (14.85%), and 2 book chapters (0.40%). Table 1 provides an overview of basic information related to this collection of publications.

Table 1. Characteristics of the selected publications.

Variable	Results
Timespan	2017:2023
Sources (journals, books, etc.)	251
Documents (articles, proceeding papers, etc.)	505
Annual growth rate %	12.25
Document average age	1.03
Average citations per documents [1]	15.14
References	25,963
Average references per documents [2]	51.41
Authors	1636
Authors of single-authored documents	26
Single-authored documents	29
Co-authors per documents [3]	4.26
International co-authorships % [4]	52.67

[1] The result of dividing the total number of citations by the number of documents. [2] The result of dividing the total number of references by the number of documents. [3] The ratio of author appearances (i.e., the total number of authors appearing in the documents, where an author appearing in two papers counts as two) to the documents. [4] The ratio of the number of documents with authors affiliated to institutions in more than one country to the total number of documents.

In Figure 2a, the evolution of research over the years is displayed. All publications in this area were published between 2017 and 2023, with a significant increase in publications in 2021 and 2022, suggesting that it is an emerging research area gaining popularity. The comparison with findings by Hajizadeh et al. [6] on the total annual scientific production in the convergence context indicates that addressing this subject in the field of smart cities started nine years later, in 2017. Nevertheless, research in this area has grown in line with the general trend [6,21], with an average annual growth rate of 12.25%, which is higher than the 7.18% average annual changes of science and engineering articles worldwide [22]. The average citation rate per year in Figure 2a indicates that publications from 2019 were cited more than others. This trend is expected as older publications tend to have more citations than recent ones, which many readers have not yet had the opportunity to read.

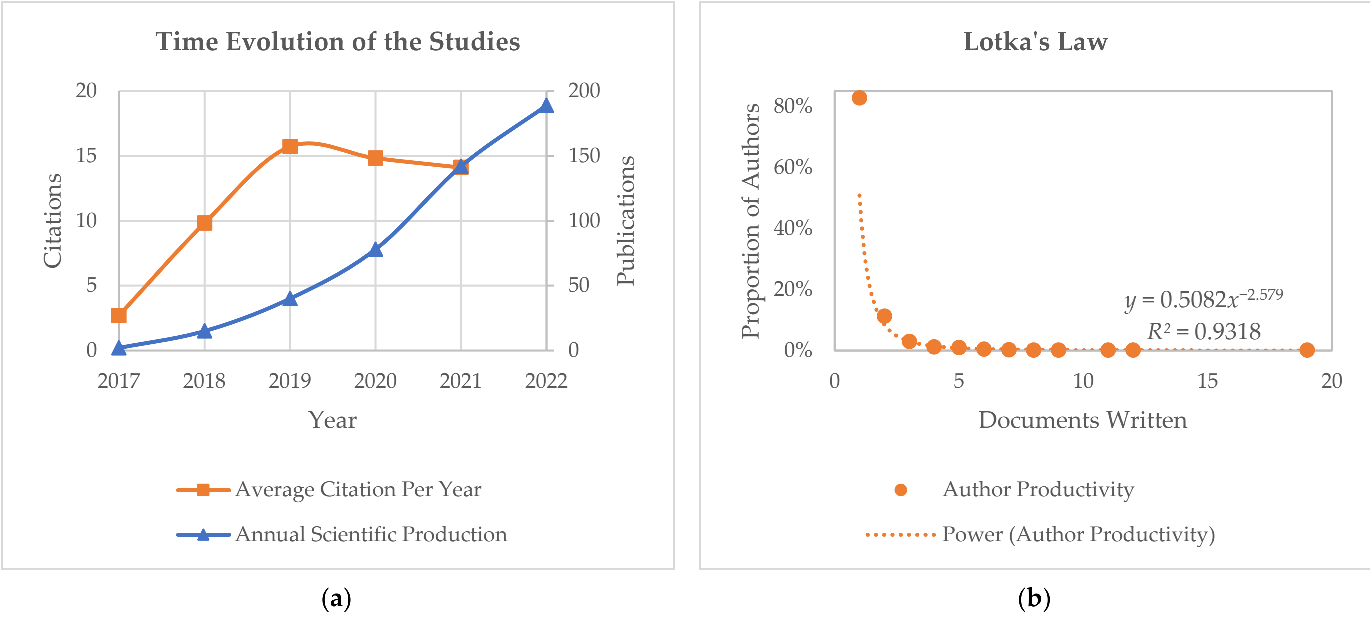

Figure 2. (**a**) Annual scientific production and average citations; (**b**) author productivity through Lotka's Law.

3.1.2. The Most Prolific Authors

The relationship between the number of authors and the documents published in the AI–blockchain research of smart cities is depicted in Figure 2b using Lotka's law, a bibliometric law describing the distribution of authors based on their productivity. The law is represented as $x^n \cdot y = c$ [23], where x represents the number of publications, y represents the number of authors who published x documents, and n ranges from 1.2 to 3.5, with c varying by field [24]. The graph indicates a high correlation (R^2 = 0.9318) between the number of authors and the publications, with $x^{2.579} \cdot y = 0.5082$ representing Lotka's law for this research domain. Notably, only 1% of the 1636 authors published more than five articles, and an adequate number of 1 to 3 authors contributed significantly (96.90%) to the research in this field.

Figure 3 measures the publication productivity of the top five authors in the subject field using four metrics. Figure 3a shows the number of publications in which each name is listed as an author. However, to account for collaboration among authors, Figure 3b presents a second measure that counts fractional publications based on the total number of authors of each paper. Figure 3a,b indicate that Tanwar S has the highest number of publications and has contributed to documents with fewer authors. Meanwhile, Gupta R's decline from second place in Figure 3a to fifth in Figure 3b confirms that most of the author's documents were produced with significant collaboration.

Figure 3c,d focus on the number of citations for documents produced by the authors, revealing several names not present in Figure 3a,b. Figure 3c presents the total citations of each author in this field, while Figure 3d shows the h-index of each author on this specific field, i.e., the number of papers they have published that have each been cited at least h times). Due to the authors' varying ranks in different metrics, some names appear interchangeably in different positions. However, Tanwar S and Park JH appear in all four figures, making them stand out as highly productive authors. Kumar N's appearance in three of the four metrics also earns the author a high ranking. These three authors can thus be considered the most prolific in the field of AI–blockchain in smart cities.

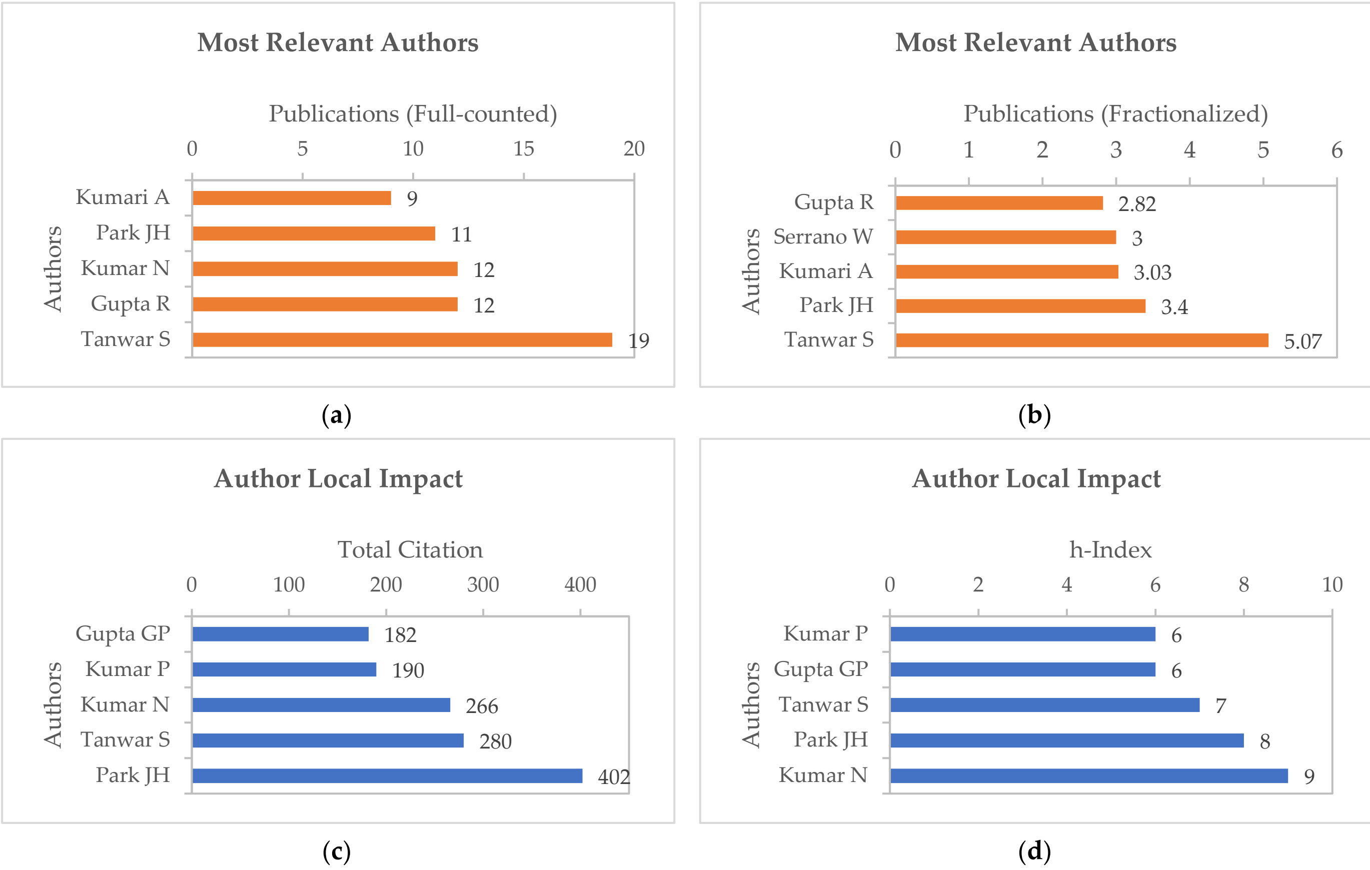

Figure 3. Authors' productivity in terms of number of documents: (**a**) full-counted; (**b**) fractionalized; (**c**) total citations; (**d**) h-index.

3.1.3. The Most Influential Sources

The study includes 505 publications from 251 sources (journals, proceedings, and book chapters). To determine the most impactful sources, Figure 4 provides four perspectives. The first perspective in Figure 4a shows the number of publications per source. Figure 4b displays the number of global citations given to local articles published in reference sources. The third perspective in Figure 4c gives the total local citations to local publications in a source, and the fourth is the sources' h-index in this particular field shown in Figure 4d. Based on all four perspectives, *IEEE Access* with an impact factor of 3.476 is the most influential journal in the field. *The IEEE Internet of Things Journal* with an impact factor of 10.238 is the second most influential source in this field, ranking second after *IEEE Access* in all perspectives except for the number of publications, where it ranks fourth. Other sources have varying interpretations based on different perspectives and can be seen in at most two subfigures with different positions.

In addition to the benefits of identifying the most influential sources, it is also valuable to determine the core sources of knowledge in a particular research area for future studies. To achieve this, we employ Bradford's law [25], which categorizes sources into three zones based on the number of publications, each containing roughly the same number of articles. Our analysis reveals that the core zone of the selected publications is comprised of 13 journals, including a total of 167 articles (representing 33% of the total number of publications), while the second and third zones consist of 72 and 166 sources, containing 172 and 166 publications, respectively. Table 2 presents the titles and specifications of the journals classified as the core sources. Additionally, it is worth noting that the core zone's citations account for 39% (equivalent to 2991 citations) of the total citations.

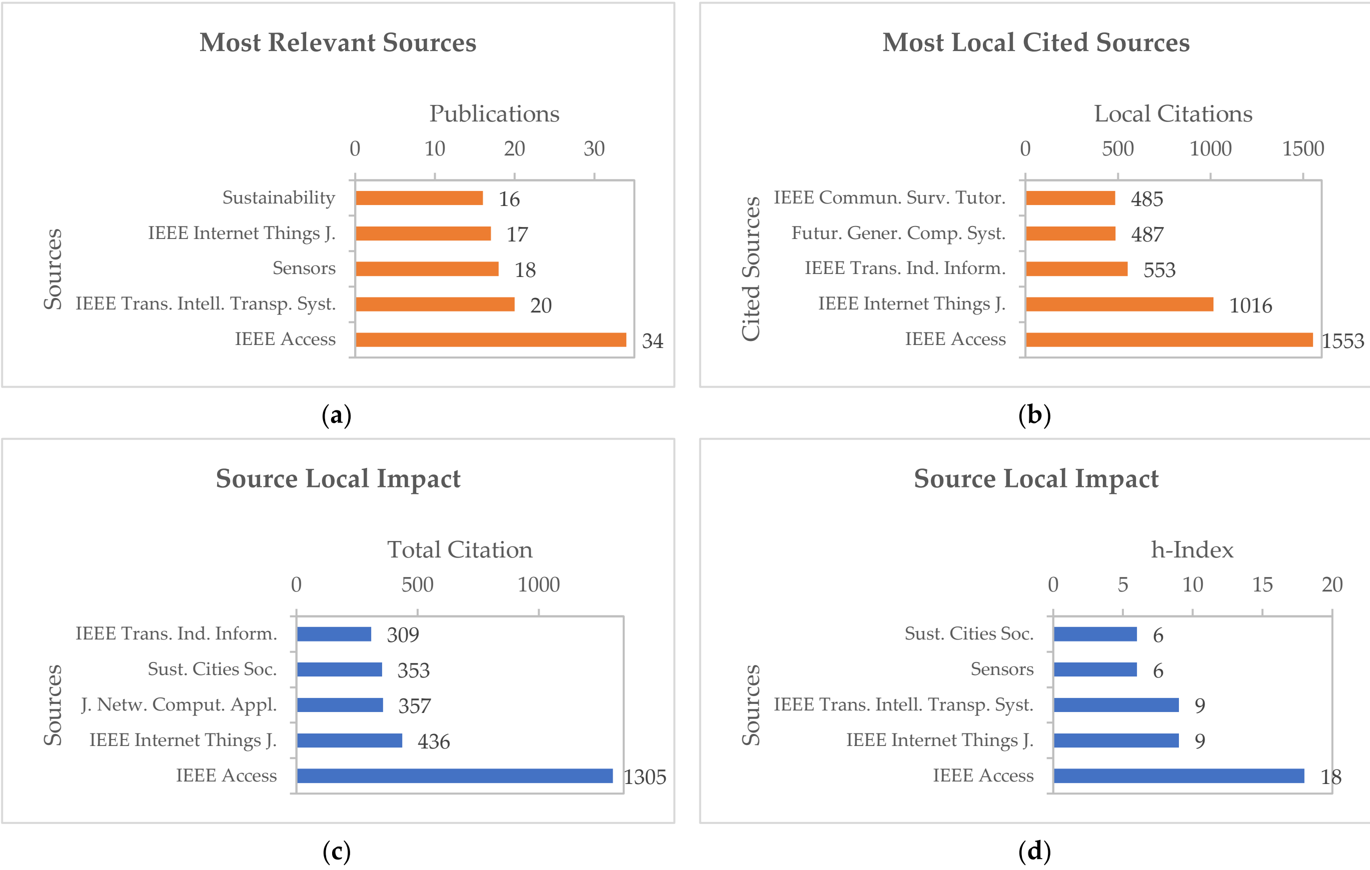

Figure 4. Sources' influence in terms of: (**a**) number of documents; (**b**) number of local citations (from reference lists); (**c**) total citations; (**d**) h-index.

Table 2. The most influential sources in the subject field.

Source	Number of Publications	Total Citations	h-Index (Local)	Impact Factor (JCR'21)
IEEE Access	34	1305	18	3.476
IEEE Transactions on Intelligent Transportation Systems	20	178	9	9.551
Sensors	18	87	6	3.847
IEEE Internet of Things Journal	17	436	9	10.238
Sustainability	16	97	4	3.251
Electronics	10	94	5	2.690
Sustainable Cities and Society	10	353	6	10.696
Applied Sciences-Basel	9	32	3	2.838
Energies	8	65	4	3.252
CMC-Computers Materials and Continua	7	5	1	3.860
IEEE Transactions on Industrial Informatics	7	309	4	11.648
Wireless Communications and Mobile Computing	6	23	3	2.146
Computational Intelligence and Neuroscience	5	7	2	3.120

3.1.4. The Most Influential Publications

Table 3 presents key information on the ten most cited publications globally. These studies were mainly published between 2019 and 2020, with an average of 4.7 authors per paper. Inter-institutional collaboration was prevalent, with nine out of ten publications being completed with such collaborations. Four of the publications are experimental research, while the rest are review articles, indicating the shift of the field from its initial stages to innovative solution production. Aggarwal et al. [26] with 15, and Allam and

Dhunny [27], and Rathore et al. [28] both with 10 citations, are the three most cited articles locally.

Table 3. The most globally cited publications in the subject field.

No.	Publication	Year	Citations
1	Klerkx et al. [29]	2019	269
2	Gai et al. [30]	2019	259
3	Fuller et al. [31]	2020	258
4	Allam and Dhunny [27]	2019	241
5	Shen et al. [32]	2019	161
6	Aggarwal et al. [26]	2019	144
7	Dorri et al. [33]	2019	143
8	Singh et al. [34]	2020	138
9	Singh et al. [8]	2020	124
10	Maddikunta et al. [35]	2022	121

3.2. Geographical Perspective of the Study Area

3.2.1. Countries' Scientific Production and Collaboration

The scientific production of documents in this field based on the authors' affiliation is depicted in Figure 5, which illustrates the collaborations between countries through thin and thick links, indicating the intensity of their joint document production. Developing countries lead the field, consistent with findings by Vu and Hartley [36] that emerging technologies have a greater impact on urban functionality, productivity, and livability in developing countries compared to developed countries, which have already made significant progress. Furthermore, smart cities utilizing digital technologies offer an ideal solution to address population pressures in developing countries, meeting the growing demand for infrastructure and services [37].

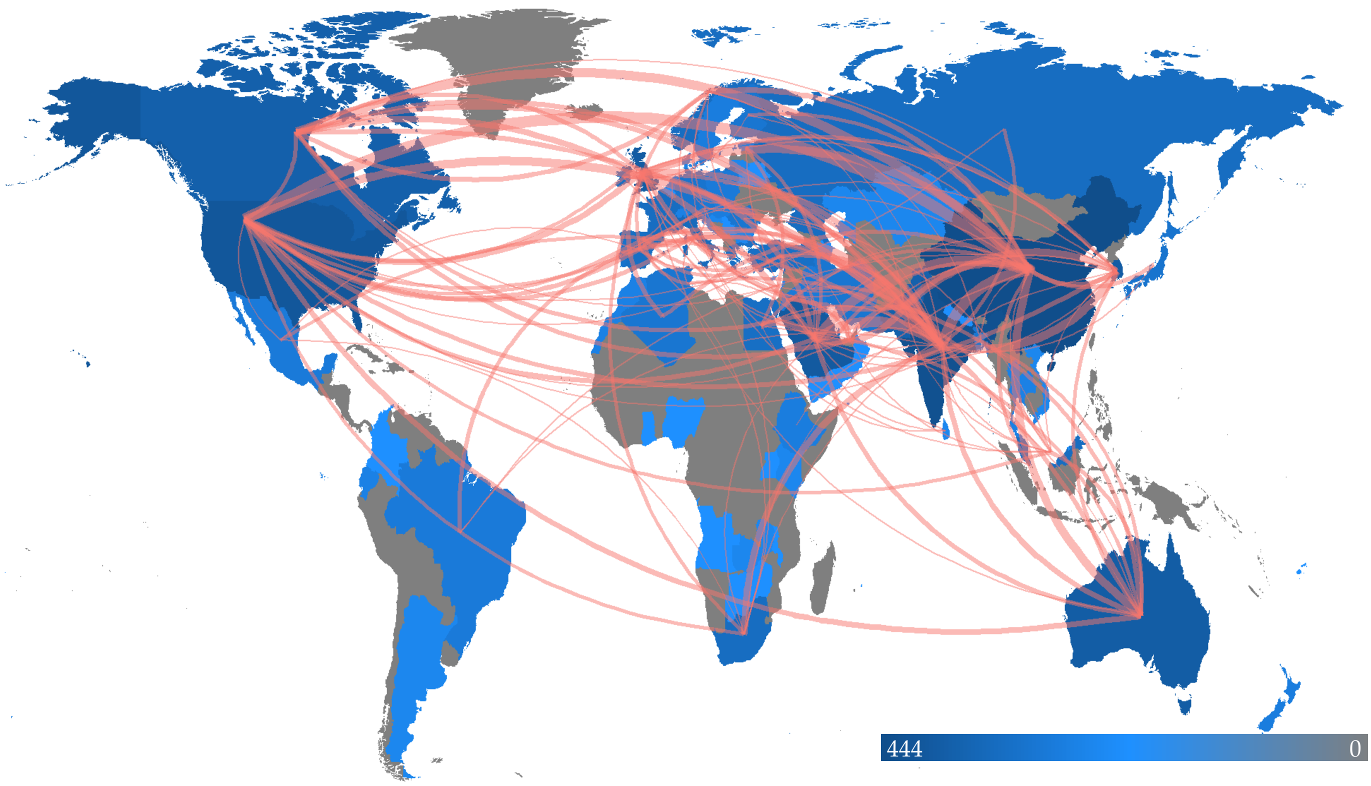

Figure 5. Scientific production in the subject area across the globe.

China has emerged as the leading producer of AI–blockchain research in the field of smart cities with 444 studies, followed by India with 338, and the United States with 156 studies, as shown in Figure 6a. These findings are consistent with the research conducted by Hajizadeh et al. [6] on countries engaged in AI–blockchain studies. While the United States had the initial lead in the scientific production in this field, as depicted in Figure 6a, it underwent a reverse process from 2019 to 2021, with a resurgence in publications in 2022.

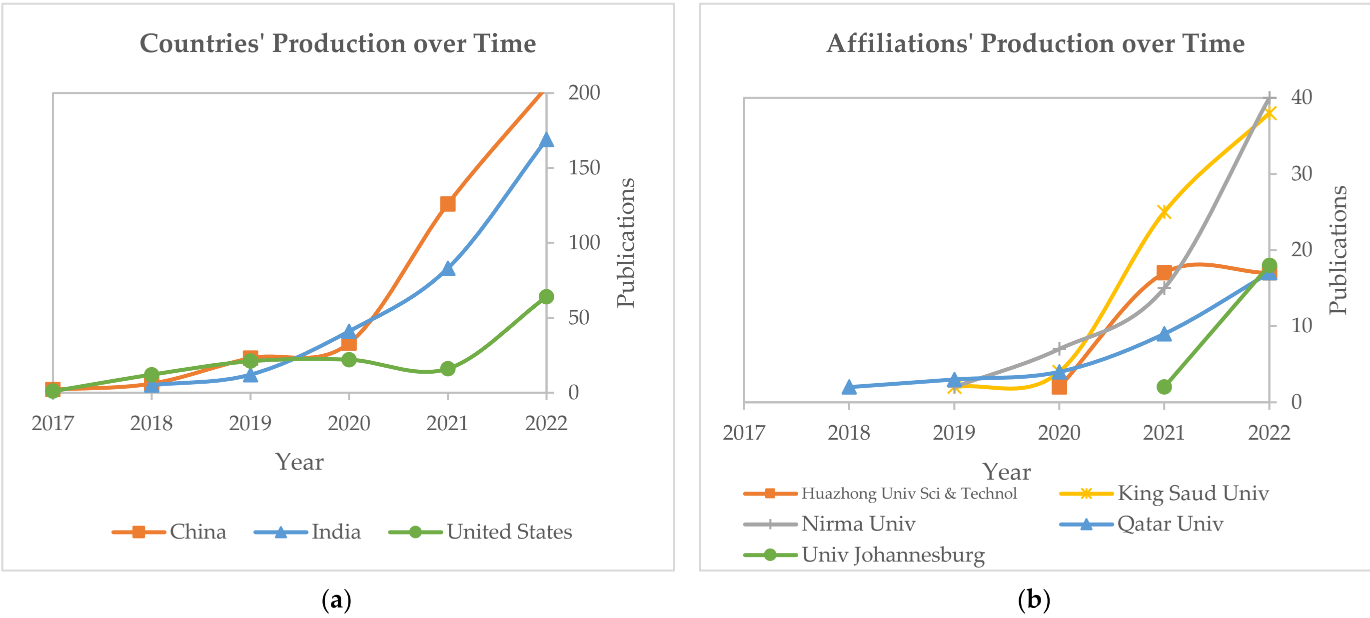

Figure 6. Evolution of scientific production by (**a**) countries; (**b**) organizations.

3.2.2. The Most Relevant Affiliations

To provide researchers in the field of smart cities with a comprehensive list of potential collaborators, we present an overview of important organizations based on their publication output. Figure 6b highlights the top five institutions among the 906 organizations involved in research in this field, with Nirma University (India) and King Saud University (Saudi Arabia) being the most productive with 42 and 41 publications, respectively, followed by the University of Johannesburg (South Africa), Huazhong University of Science and Technology (China), and Qatar University (Qatar). When considering the location of the top 100 universities or institutions, China has the largest share at 17%, followed by India with 15%, and South Korea with 10%, while the majority of the remaining institutions are located in Saudi Arabia, Australia, the United States, and the United Kingdom.

Figure 6b highlights the research performance of the top five institutions in the field of AI–blockchain research in smart cities. Qatar University shows a gentle slope compared to other organizations, indicating their early entry into this field. Nirma University and King Saud University entered the field in 2019 and have since maintained a strong research output, each publishing more than 40 articles on coupling AI and blockchain in smart cities. It is noteworthy that Huazhong University of Science and Technology's research output in this field declined in 2022 after a strong rise between 2020 and 2021. The University of Johannesburg can be considered a new entrant in this field, as they have been publishing at a favorable rate since 2021.

3.3. Social Perspective of the Study Area

3.3.1. Co-Authorship Network

This paper conducts an analysis of authors and their collaborative relationships in the field of AI–blockchain in smart cities by examining 505 pieces of related literature. The co-authorship network is generated using CiteSpace with the following parameters:

a scale factor of $k = 100$ ($k \in \mathbb{Z}^+$) used in the calculation of the modified g-index [38] ($g^2 \leq k \sum_{i \leq g} c_i$), a link retaining factor (LRF) of -1 (unlimited), and a lookback year (LBY) of -1 (unlimited) for the years 2017 to 2023. The resulting network consists of 589 nodes (authors) and 888 links (co-authorship), with the largest clusters shown in Figure 7. The thickness of the link between two nodes indicates the level of co-authorship. The three most cited authors in each cluster are highlighted, and the clusters are named using the log-likelihood ratio (LLR) algorithm [39] based on the keywords of articles published by authors in that cluster.

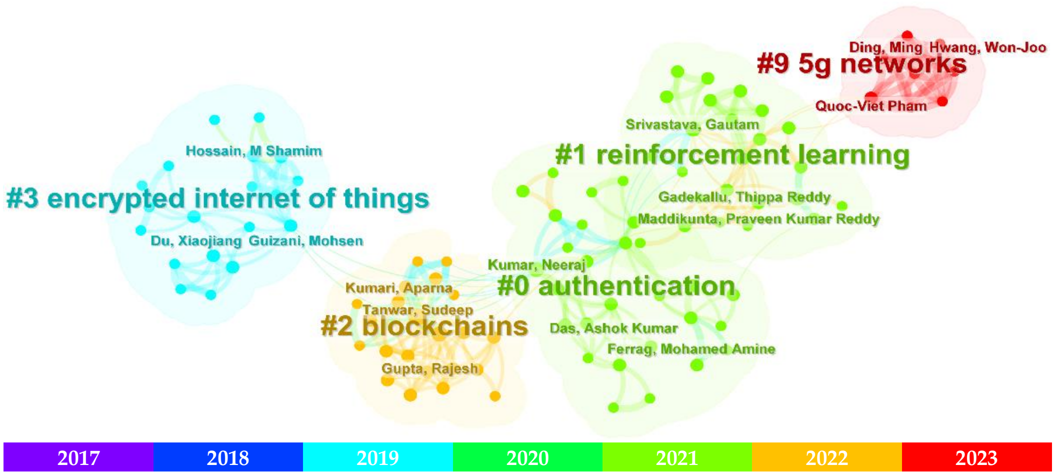

Figure 7. Largest co-authorship clusters in the subject field.

Out of the top five authors listed in Section 3.1.2, three authors (Tanwar S, Gupta R, and Kumari A) belong to cluster #2, which suggests that their primary focus is on blockchain. Collaboration between authors in this cluster has increased since 2022, as shown by link color. The next highest-ranked author, Kumar N, is in cluster #0, where research is focused on authentication and published mainly in 2020. Park JH is in cluster #6, not shown in Figure 7 due to a small number of co-authors. Network density in terms of collaborative relationships is low at 0.005, indicating a lack of strong connections between authors. Tanwar S has the highest degree (i.e., number of co-authorship relationships) in cluster #2 with a degree of 22, followed by Kumar N in cluster #0 with a degree of 19, Gupta R in cluster #2, and Gadekallu T in cluster #1 with a degree of 16, and Srivastava G in cluster #1 with a degree of 14.

In terms of network structure, the modularity Q of 0.938 indicates a high degree of division into loosely coupled clusters, and the mean silhouette score of 0.943 suggests high homogeneity within these clusters. However, nodes with high betweenness centrality are limited, with Kumar N (0.03), Guizani M (0.02), Tanwar S (0.01), Gadekallu T (0.01), and Srivastava G (0.01) having the highest scores, respectively. Figure 7 shows that Kumar N plays a pivotal role in connecting clusters #0, #1, #2, and #3 mainly in 2019, so that the only connection of clusters #0 and #3 is due to this author's co-authorship with Guizani M. Guizani M is also the connecting node between clusters #3 and #2. Lastly, Pham QV is the author who establishes the link between cluster #1 and #9. The co-authorship relationships between researchers in cluster #9 and those in other clusters, particularly cluster #3, may not have been formed yet due to the novelty of publications in cluster #9.

Table A1 (see Appendix A) provides detailed characteristics of the five clusters identified in Figure 7. It is evident from the table that in cluster #0, scholars are primarily focusing on authentication mechanisms in blockchain platforms, particularly in the context of smart agriculture. Reinforcement learning, especially in the field of privacy in energy and transportation systems, is the main area of research for authors in cluster #1. The different labels proposed by latent semantic indexing (LSI) [40], mutual information (MI) [41], and LLR algorithms highlight the focus of cluster #2 on the use of blockchain in healthcare and Industry 4.0. The use of encrypted IoT in conjunction with machine learning and consortium blockchains to enhance privacy is the primary topic of interest for authors in cluster #3. Lastly, cluster #9 is solely dedicated to exploring 5G technology in smart cities.

3.3.2. Co-Authors' Institutions Network

A network of co-authors' institutions is created to explore the core institutions and cooperation relationships in the field of AI–blockchain in smart cities. We set up CiteSpace parameters as follows: $k = 100$, LRF = −1, and LBY = −1, resulting in a network of 504 nodes and 804 links, with node size indicating centrality score and the thickness of connections indicating the frequency of cooperation between institutions. The largest clusters are shown in Figure 8, with a modularity Q of 0.829 indicating proper clustering and a mean silhouette score of 0.942 indicating high homogeneity. However, the low network density of 0.006 suggests weak relationships between organizations in this field. The largest cluster consists of 34 organizations, representing less than 7% of the total network nodes. Critical institutions in the network can be identified from Figure 8. Two institutions, King Saud University in cluster #3 with centrality of 0.22 and Taif University in cluster #0 with centrality of 0.11, have betweenness centrality greater than 0.1 and are located at structural holes. King Saud University connects cluster #3 to clusters #0, #1, #2, #8, and #9 through links with 35 other academic institutions, while Taif University connects cluster #0 to clusters #3, #5, and #6 through links with 15 other academic institutions.

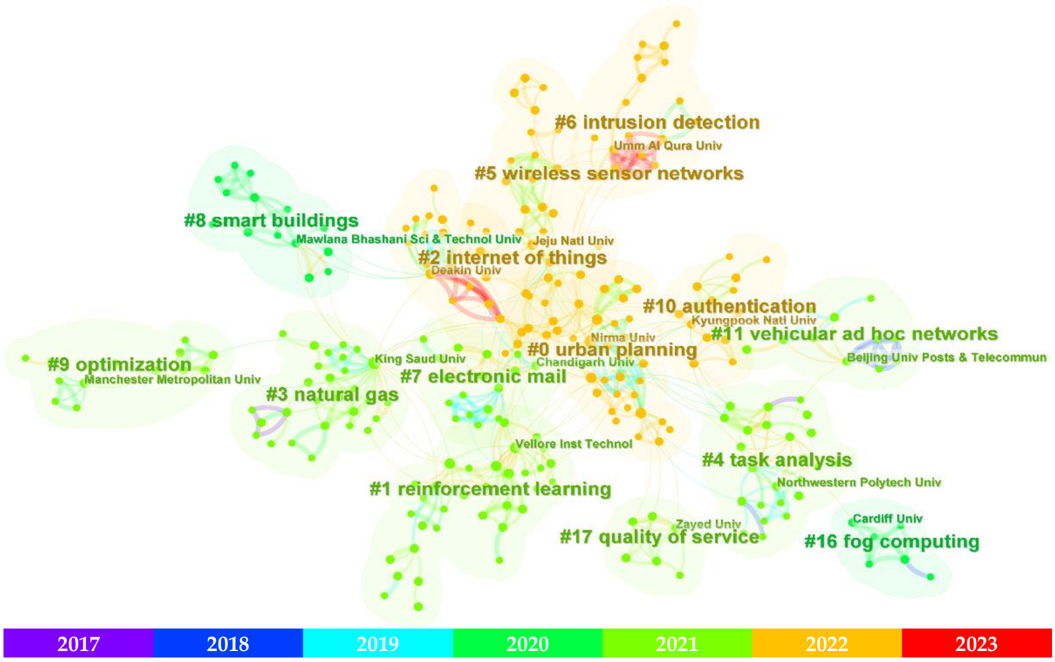

Figure 8. Largest co-authors' institutions clusters in the subject field.

3.4. Conceptual Perspective of the Study Area

3.4.1. Co-Occurring Keywords Network

Keywords are condensed representations of academic publications that provide high-level summaries of the content, increasing visibility and understanding of the study's core and focus [42]. Co-word analysis is a method that utilizes the co-occurrence of keywords to reveal the conceptual structure of a research field. In this study, the configuration parameters for CiteSpace are set as $k = 100$, LRF = −1, LBY = −1. In addition, the minimum number of links per node is set as e = 1, and a pathfinder algorithm is used to prune the merged co-occurrence network map. The clusters detected in the network of co-occurring keywords, with 504 nodes, 961 links, and density of 0.008, are shown in Figure 9. The size of nodes indicates their centrality, and the color of linkages shows when two keywords first appeared in the same paper. The modularity Q of 0.887 and the mean silhouette score of 0.964 indicate proper clustering and high homogeneity of the clusters.

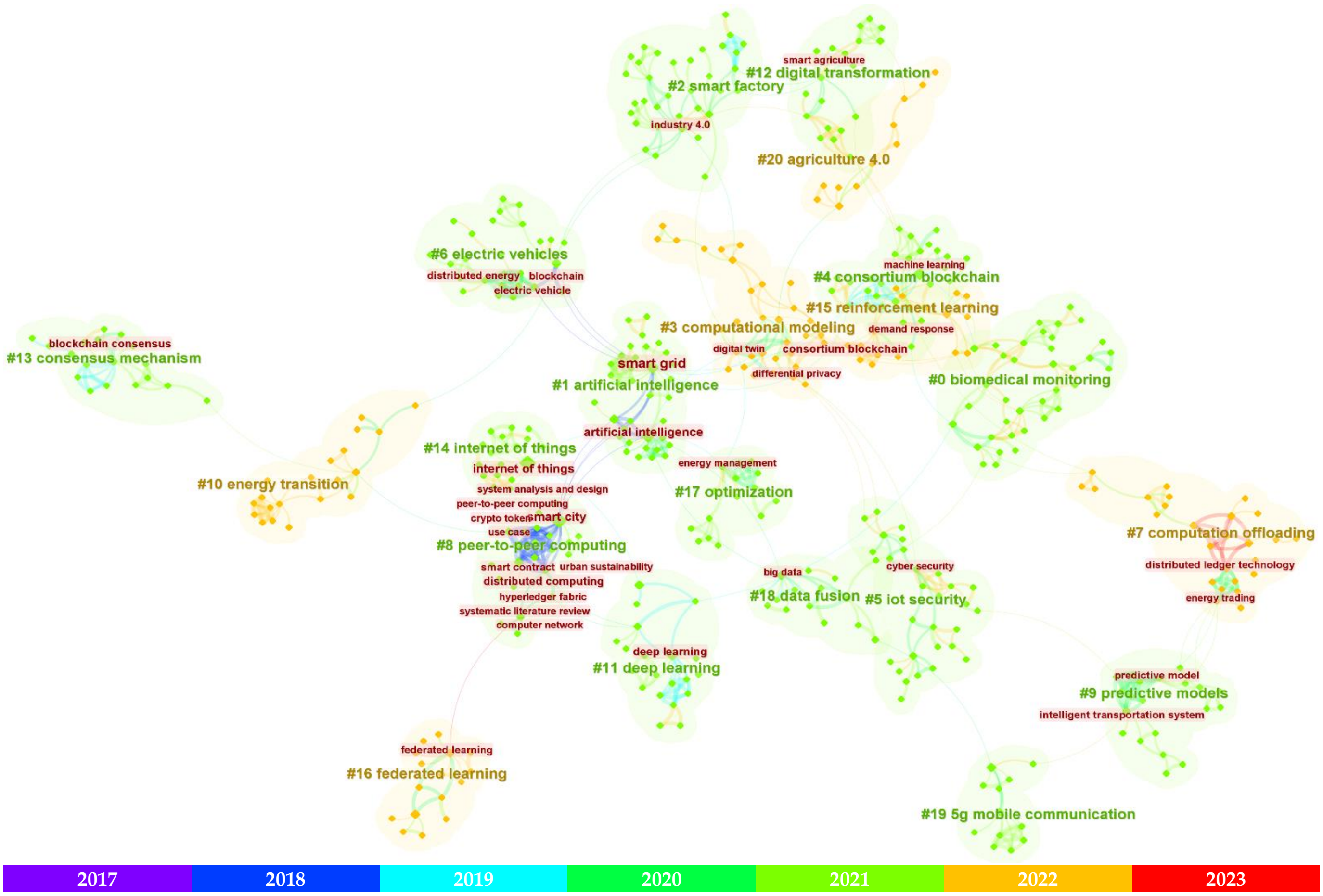

Figure 9. Largest keywords' co-occurrence clusters in the subject field.

In Figure 9, keywords with over 10 repetitions are shown in addition to the identified clusters. Despite cluster #0 being the largest, the most frequent keyword belongs to cluster #8, which centers on peer-to-peer computing. Internet of Things ranks first in frequency with 104 occurrences since 2019, followed by smart city and artificial intelligence with 73 and 55 occurrences, respectively, since 2018. However, the importance of keywords is not solely based on their frequency, but also on their betweenness centrality in the network. Table A2 (Appendix A) compares the subject names proposed by three algorithms: LSI, MI, and LLR for naming clusters. Cluster #8 contains the oldest co-occurring words that have been observed as related keywords in several articles since 2019. The largest cluster (#0) concentrates on biomedical monitoring and the application of edge learning in this field, while the smallest one (#20) focuses on the digitization and smartening of agriculture for the fourth revolution.

Table 4 lists the top ten keywords with the highest centrality, and all nodes have a centrality greater than 0.1. The keyword with highest centrality (0.63) is smart grid in cluster #1, which connects this cluster to cluster #3, #4, and #6 through co-occurrence with differential privacy, neighboring energy trading, consortium blockchain, blockchain, electric vehicle, and adaptive charging scheme. The remaining 21 keywords that co-occur with smart grid are all located in cluster #1, acting as connection points between this cluster and clusters #3, #8, #14, and #18.

Table 4. Top ten keywords with highest betweenness centrality.

No.	Keyword	Frequency	Degree	Centrality	Year	Cluster
1	smart grid	65	27	0.63	2018	1
2	artificial intelligence	77	20	0.57	2018	1
3	differential privacy	8	10	0.41	2019	3
4	smart city	88	19	0.35	2018	8
5	cybersecurity	20	10	0.29	2020	5
6	blockchain	283	11	0.28	2018	6
7	distributed computing	3	13	0.24	2018	8
8	digital twin	7	10	0.24	2019	3
9	real-time system	6	9	0.24	2020	10
10	consortium blockchain	4	13	0.22	2019	4

Categorizing the most frequent keywords into five categories of blockchain, AI, smart cities, security, and IoT, as illustrated in Figure 10, the blockchain category has the highest occurrence, appearing in 35% of the publications. It is followed by the AI keywords, such as artificial intelligence, machine learning, and related methods, which appear in 19% of the publications. In comparison, the topic of smart cities appears in fewer publications than the other categories, indicating a comparatively lower level of interest.

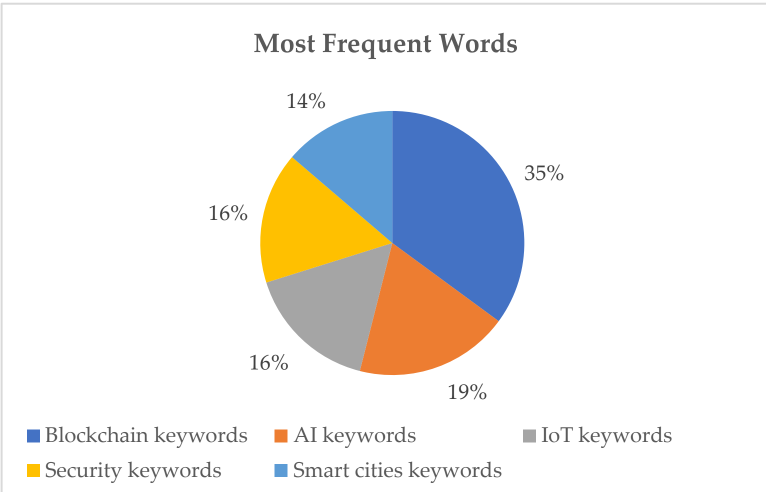

Figure 10. Most frequent authors' keyword categories.

3.4.2. Keyword Burst Analysis

Significant increases in the frequency of keywords during a relatively short period of time usually reflect research foci and are therefore of particular interest to the scientific community as indicators to identify emerging research trends [43]. Table 5 shows the result of keyword burst detection to identify research hotspots of the AI–blockchain integration in the field of smart cities. From Table 5, seven keywords with bursts of at least one year are detected. In chronological order, the keyword bursts have been changing over the years from 2019 to 2023, indicating a dynamic research landscape in this field.

Furthermore, the sigma composite metric, which measures scientific novelty by analyzing the combined strength of the structural and temporal properties of nodes, can identify keywords that likely represent new ideas [44]. As shown in Table 5, the first five keywords have burst among researchers at some point in the past years, making them research hotspots during the corresponding periods. Federated learning and collaborative work began to burst in 2022 and continue to be research hotspots currently. Given its relatively high centrality (0.11) and moderate co-occurrence with other keywords (degree of 11), we believe that federated learning has a greater potential to emerge as a research trend in integration with blockchain-related topics in the field of smart cities.

Table 5. Keywords with burst of at least one year.

No.	Keyword	Year	Strength	Begin	End	Sigma	2017–2023
1	consortium blockchain	2019	1.86	2019	2019	1.44	
2	big data	2019	1.63	2019	2019	1.28	
3	security and privacy	2020	3.52	2020	2020	1.34	
4	energy internet	2020	1.57	2020	2020	1.00	
5	peer-to-peer network	2020	1.57	2020	2020	1.00	
6	federated learning	2020	2.29	2022	2023	1.27	
7	collaborative work	2022	1.80	2022	2023	1.00	

3.4.3. Text Processing of Terms

The WoS dataset provides four text fields for each bibliographic record: title, abstract, author keywords, and keywords plus. To better define the concept [45], we analyze the first two unstructured text fields (i.e., title and abstract) in addition to the keywords studied in Section 3.4.1 since they contain a higher frequency of relevant terms than keywords [46]. CiteSpace is configured with parameters k = 50, LRF = −1, LBY = −1, and e = 1, as well as a pathfinder algorithm that prunes the co-occurrence merged network map. The resulting network includes 557 terms in 15 clusters connected through 2016 links, with a density of 0.013, modularity Q of 0.844, and the weighted mean silhouette of 0.918. Figure 11 displays this network and identifies clusters, where node size indicates frequency and color spectrum represents repetition in different years.

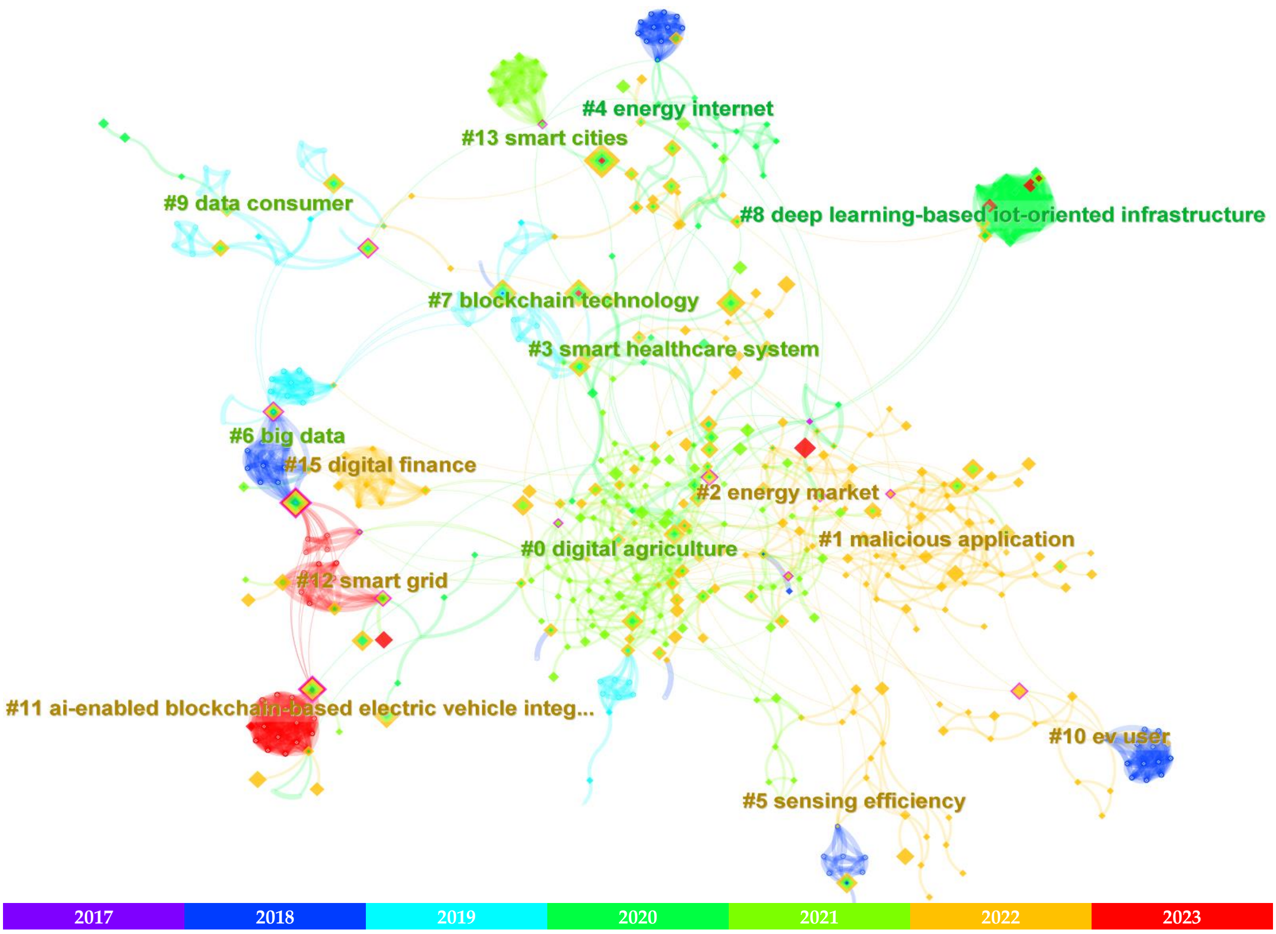

Figure 11. Largest terms' co-occurrence clusters in the subject field.

Cluster #0 on digital agriculture is the largest with 105 nodes and a silhouette score of 0.823. The nodes with the highest frequency (88) and centrality (0.30) are artificial intelligence in cluster #6 and adaptive service level agreement in cluster #2. The most recent bursting term in this field is smart factories in cluster #2 (focused on the energy market), which started bursting in 2022 with a strength of 2.28 and a sigma of 1.00. Smart factories is connected to the Industrial Internet, which in turn is connected to the IoT system and data management in the network.

3.5. Intellectual Perspective of the Study Area

3.5.1. Author Co-Citation Network

An author co-citation network is utilized to identify areas of expertise that are widely recognized by research communities in the field of AI–blockchain in smart cities. Co-citation occurs when two references are cited by a third reference. The articles retrieved from WoS in this field cite 25,963 publications with one or more authors, as shown in Table 1. To perform this analysis, CiteSpace parameters are set to k = 25, LRF = −1, LBY = −1, and e = 1. The merged network is pruned using a pathfinder algorithm, resulting in a network of 453 nodes and 1192 links. A node's size represents the number of citations an author has received, while the thickness of the link between two nodes indicates how many times two authors have been cited together in the same articles. A network density of 0.012 indicates that strong co-citation relationships have yet to be formed in this field.

Figure 12 presents the main clusters identified in this author co-citation network. The network has a high modularity Q of 0.825 and a high mean silhouette score of 0.931. The LLR algorithm is used to name the clusters based on the keywords of the articles that have cited at least two nodes of the network simultaneously. Figure 12 also displays the three most cited authors in each cluster. To investigate the connections between different clusters, nodes with a high betweenness centrality score can be examined. However, in this network, only 13 nodes have a centrality greater than or equal to 0.1.

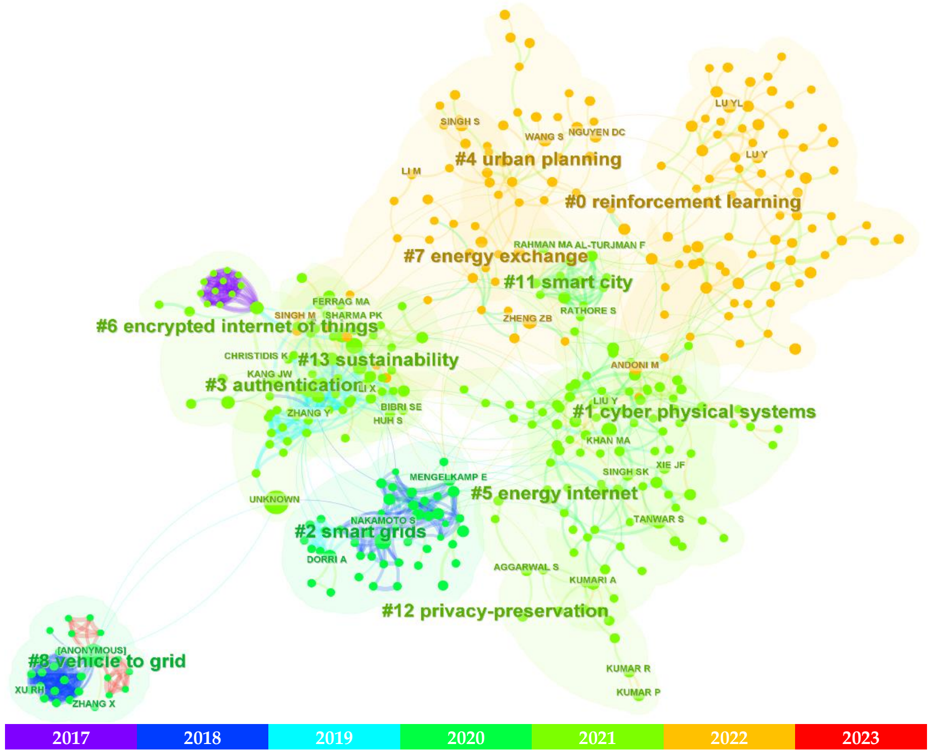

Figure 12. Largest author co-citation clusters in the subject field.

The co-cited authors in this field include Nakamoto S in cluster #2 (59 co-citations since 2018), Sharma PK in cluster #3 (48 co-citations since 2019), and Ferrag MA in cluster #6

(45 co-citations since 2019). The most influential nodes in terms of betweenness centrality are Allam Z (0.24, 2018) in cluster #2, Kim M (0.20, 2021) in cluster #4, and Grieves M (0.17, 2021) in cluster #0. Allam Z provides scientific references for multi-disciplinary publications focusing on smart grids combined with topics such as cyber physical systems, energy internet, energy exchange, and sustainability by co-citing with scholars in clusters #1, #5, #7, and #13. Kim M contributes to the preparation of documents focusing on urban planning in combination with the topics of reinforcement learning, energy exchange, and sustainability along with the publications of authors in clusters #0, #7, and #13. Grieves M links cluster #0 with clusters #1, #2, and #3, focusing on combining reinforcement learning with topics such as cyber physical systems, smart grids, and authentication.

3.5.2. Journal Co-Citation Network

A journal co-citation network is generated to analyze the source of publications and detect the most representative cited journals in the field of AI–blockchain integration in smart cities. CiteSpace is configured with parameters $k = 25$, LRF = −1, LBY = −1, and e = 1, and a pathfinder algorithm is used to prune the merged network. Figure 13 shows the resulting network, which has 491 nodes and 1100 links with a density of 0.009. Larger nodes indicate more references to the source, and thicker links between two nodes indicate more times the two sources are cited together. While the frequencies of the nodes confirm the findings shown in Figure 4b and the order of the journals, the betweenness centrality scores largely differ from this order.

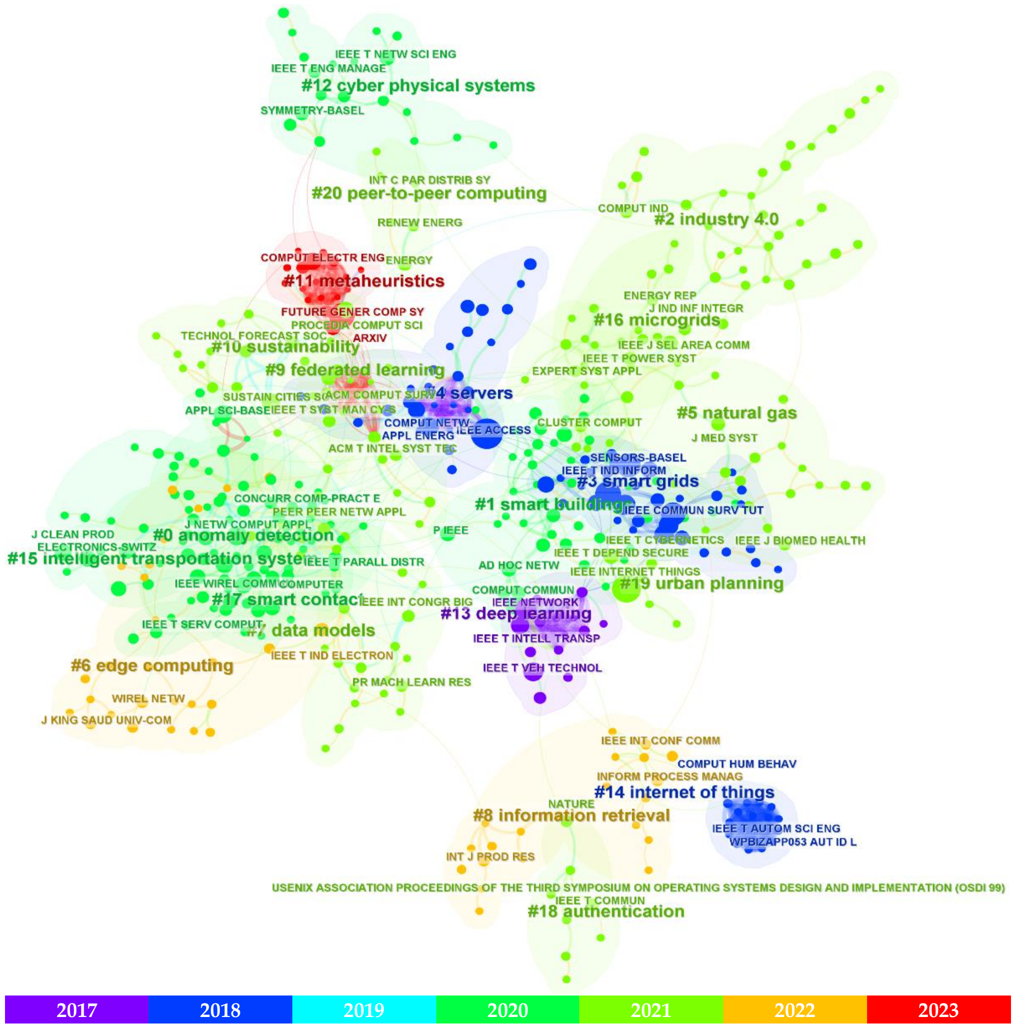

Figure 13. Largest source co-citation clusters in the subject field.

Figure 13 illustrates the main clusters identified in the journal co-citation network analysis of AI–blockchain integration in smart cities. The modularity Q is 0.822 and the weighted mean silhouette score is 0.929. Additionally, the three most cited sources within each cluster are presented. Clusters are named using the LLR algorithm, which takes into account the keywords of the articles that cite at least two network nodes simultaneously. Cluster #0 is the largest cluster in the network, consisting of 68 sources, followed by clusters #1 and #2 with 46 and 38 sources, respectively. These three clusters together make up 31% of the sources in this field. The three most frequently cited sources in terms of journal co-citation are *IEEE Access* (330, 2017), *IEEE Internet of Things Journal* (269, 2018), and *IEEE Transactions on Industrial Informatics* (205, 2018). *IEEE Access* is in cluster #4, which mainly focuses on servers and microgrids. *IEEE Internet of Things Journal* is in cluster #19, where urban planning is the main focus. *IEEE Transactions on Industrial Informatics* is in cluster #3. Documents that refer to sources within this cluster are generally in the field of smart grids.

Table 6 lists the top ten sources with the greatest betweenness centrality based on co-citation analysis. The sources include journals and conference proceedings, with most of them located in clusters #4 and #0. These clusters focus on topics such as servers, microgrids, and anomaly detection.

Table 6. Top ten co-cited sources with the highest betweenness centrality scores.

No.	Source	Frequency	Degree	Centrality	Year	Cluster
1	*Communications of the ACM*	33	20	0.33	2017	4
2	*IEEE Transactions on Knowledge and Data Engineering*	21	18	0.31	2019	0
3	*Applied Energy*	68	20	0.29	2017	4
4	2017 IEEE 24th International Conference on Web Services (ICWS 2017)	3	14	0.25	2020	1
5	*IEEE Access*	330	14	0.22	2017	4
6	*IEEE Transactions on Smart Grid*	78	13	0.21	2018	3
7	*ACM Transactions on Intelligent Systems and Technology*	33	13	0.21	2019	9
8	2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)	14	10	0.21	2019	0
9	IEEE International Conference on Systems, Man, and Cybernetics (SMC)	13	9	0.19	2019	0
10	2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)	16	18	0.18	2017	13

3.5.3. Document Co-Citation Network

To identify relevant literature on AI–blockchain convergence in smart cities and visualize research gaps, we conduct a document co-citation analysis using CiteSpace with parameters set as $k = 25$, LRF = −1, LBY = −1, and e = 1, and pruned the network using a pathfinder algorithm. The resulting network consists of 376 nodes and 1117 links with a density of 0.016, as shown in Figure 14. Considering that in our analysis the betweenness centrality of nodes is more important than their co-citation frequency, in Figure 14 we consider the size of nodes as a proxy for their centrality score. Furthermore, we show the top ten publications in terms of centrality with a score greater than 0.1 in the figure, in their respective clusters. The modularity Q of 0.838 and weighted mean silhouette of 0.922 indicates proper clustering and high homogeneity of the clusters, respectively. In addition, Table A3 in Appendix A provides details of the clusters and the topics covered by them.

The clusters in Figure 14 and Table A3 have similar titles to those shown in Figures 7–9 and 11–13, indicating that most of the research areas in the field of AI–blockchain in smart cities have already been explored. However, cluster #4 covers completely new ideas related to the 6G network and the 5th industrial revolution based on blockchain, making it an important trend to watch. Cluster #7 focuses on the key agreement protocol, which is an authentication protocol that allows communication parties to agree on a key that influences the outcome. On the other hand, cluster #15 covers volunteer computing, a distributed computing topic that involves providing processing power or storage from personal devices to assist processes that require significant computing power. While not a new trend in the field, volunteer computing has been around since the 1990s [47,48] and is seen as an enabler for edge computing [49].

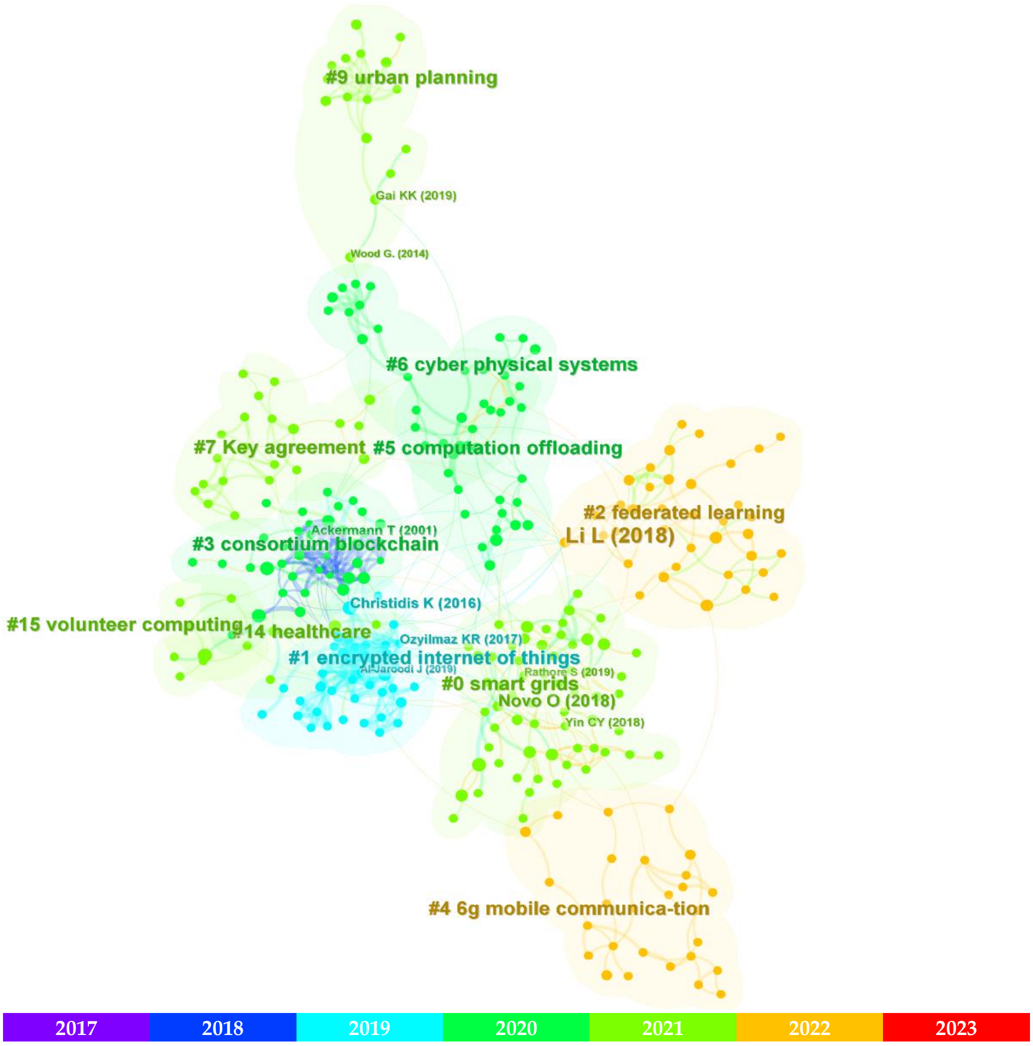

Figure 14. Largest document co-citation clusters in the subject field.

Figure 15 presents a timeline view of the clusters, illustrating the origin, evolution, and time span of each cluster. The members of each cluster are shown in chronological order along the horizontal axis, while the clusters are displayed vertically from top to bottom according to their size. The disappearance of a cluster in recent years may indicate that researchers prefer to explore new research directions rather than focusing on the vanished domain. From this perspective, it appears that the co-citation of publications in clusters #1, #3, and #14 (i.e., encrypted IoT, consortium blockchain, and healthcare) has ceased since 2020 and earlier, and instead, the new trend is to co-cite publications included in clusters #0 and #2 (i.e., smart grids and federated learning).

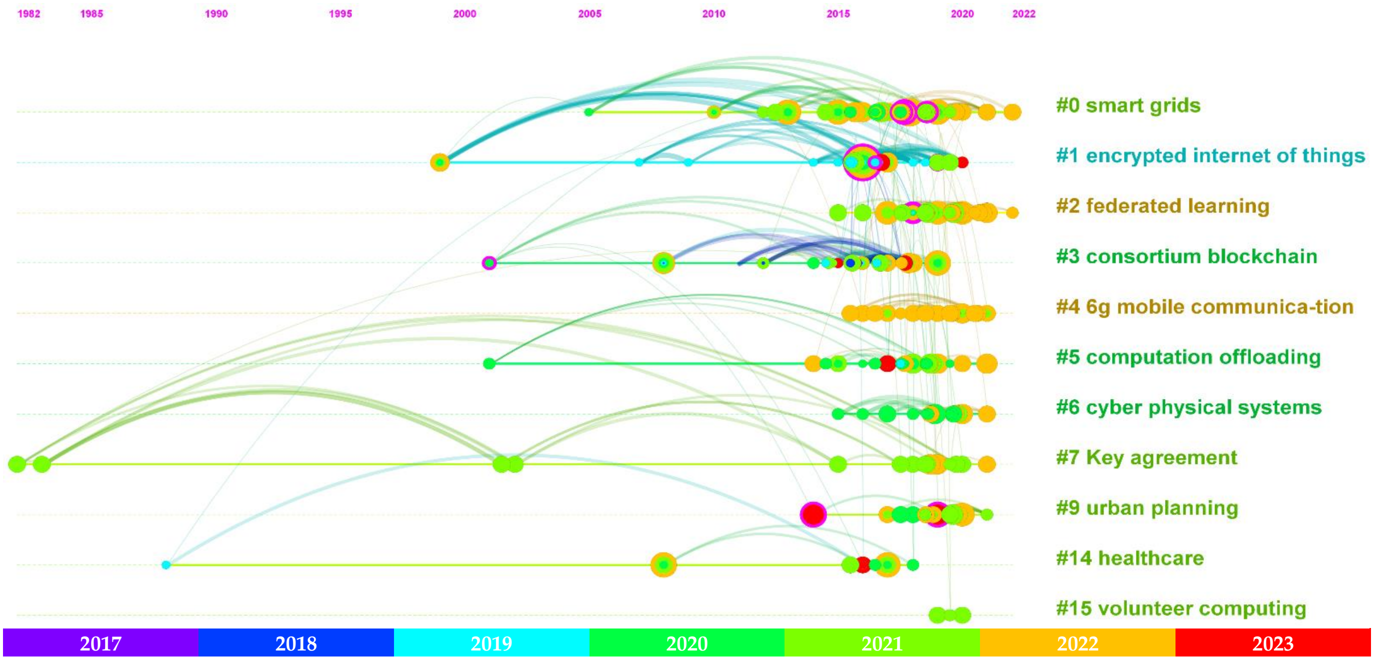

Figure 15. Timeline visualization of the largest document co-citation clusters in the subject field.

Table 7 lists the top ten nodes in the network, ranked according to centrality. As evident from the table, most of these documents are found in clusters #0 and #1, with each cluster containing three documents that focus on smart grids and the IoT. Cluster #9, which is related to urban planning, is ranked next with two highly central nodes. We further analyze the first three articles listed in Table 7. Li et al. [50] has been co-cited with publications in clusters #1, #2, #3, #5, and #7, with the highest number of co-citations coming from cluster #1, indicating that the integration of federated learning and IoT is a popular topic among scholars citing this article. Novo [51] has been co-cited with publications in cluster #0, #1, #4, and #5, with the highest number of co-citations coming from cluster #1, indicating that the integration of smart grids and IoT is a popular topic among scholars citing this article. Christidis and Devetsikiotis [52] have been co-cited with publications in cluster #1, #2, #3, #5, and #7, with the highest number of co-citations coming from cluster #3, indicating that the integration of consortium blockchain and IoT is a popular topic among scholars citing this article.

Table 7. Top ten co-cited documents with the highest betweenness centrality scores.

No.	Publication	Year	Frequency	Degree	Centrality	Cluster
1	Li et al. [50]	2018	9	13	0.23	2
2	Novo [51]	2018	11	9	0.18	0
3	Christidis and Devetsikiotis [52]	2016	31	14	0.16	1
4	Oezyilmaz and Yurdakul [53]	2017	2	21	0.14	1
5	Ackermann et al. [54]	2001	2	6	0.14	3
6	Gai et al. [30]	2019	12	4	0.13	9
7	Yin et al. [55]	2017	5	10	0.13	0
8	Rathore et al. [28]	2019	5	13	0.12	0
9	Wood [56]	2014	11	2	0.11	9
10	Al-Jaroodi and Mohamed [57]	2019	5	15	0.11	1

3.5.4. Bursts in the Network of Document Co-Citations

We detect citation bursts to determine whether and when the number of citations of a particular reference has significantly increased and if a particular connection has been strengthened within a short period of time [39]. In other words, we seek to identify statistically significant fluctuations during a short time interval within the overall time period in documents' citations. Table 8 presents the top 12 references with the strongest citation bursts lasting more than two years between 2017 and 2023, which can be regarded as major milestones in the development and evolution of the AI–blockchain convergence in smart cities. Additionally, by examining of the combined strength of the structural and temporal properties of nodes, sigma identifies publications that likely represent new ideas [44] and measures nodes' scientific novelty.

Table 8. Top 12 references with the strongest citation bursts.

No.	Publication	Year	Strength	Begin	End	Sigma	2017–2023
1	Li et al. [58]	2017	3.1	2018	2020	1.06	
2	Swan [59]	2015	2.71	2018	2020	1.02	
3	Yli-Huumo et al. [60]	2016	2.71	2018	2020	1.01	
4	Aitzhan and Svetinovic [61]	2016	2.37	2018	2019	1.05	
5	Sharma et al. [62]	2017	4.37	2019	2020	1.1	
6	Tschorsch and Scheuermann [63]	2016	3.05	2019	2020	1.1	
7	Sharma et al. [64]	2017	2.61	2019	2020	1.1	
8	Dorri et al. [65]	2017	2.61	2019	2020	1.02	
9	Dorri et al. [66]	2017	2.61	2019	2020	1.03	
10	Li et al. [67]	2020	2.18	2019	2020	1.21	
11	Gai et al. [30]	2019	2.44	2020	2021	1.34	
12	Wood [56]	2014	2.24	2020	2021	1.27	

According to Table 8, the focus of key milestones from 2017 to 2023 can be summarized as follows:

1. *Reviews*: There are four reviewed works, including one book and three literature reviews. The book by Swan [59] explores how the blockchain is becoming a new disruptive computing paradigm beyond its traditional uses for currency (Blockchain 1.0) and smart contracts (Blockchain 2.0). Tschorsch and Scheuermann [63] examine the fundamental structures and insights at the core of the Bitcoin protocol, proposing key ideas that are applicable to various fields. Yli-Huumo et al. [60] review 41 scientific articles through a systematic mapping study, finding that less than 20% of the articles focus on smart contracts and licensing. The authors recommend future research directions and highlight security and privacy concerns as the most important issues in the blockchain field. Li et al. [67] conduct a systematic review of blockchain security threats, analyzing actual attacks on popular blockchain systems and suggesting future directions in this field;
2. *Conceptual designs*: Wood [56] presents a design document outlining the implementation of Ethereum using blockchain technology, which allows for secure transactions and acts as a transactional singleton machine with a shared state. The document covers the system design, implementation issues, potential benefits, and expected obstacles. Dorri et al. [66] propose a blockchain-based architecture as a solution to address security and privacy concerns in a smart vehicular ecosystem, including location tracking and remote hijacking. The architecture leverages wireless remote software updates and dynamic vehicle insurance fees to demonstrate its effectiveness against common security attacks. Sharma et al. [64] introduce Block-VN, a blockchain-based vehicular network architecture designed for smart cities. They demonstrate the architecture's security and reliability, and its potential to build a distributed transportation management system. They also analyze the evolution of vehicular networking with

network-centric and vehicular information paradigms, and provide design principles and service scenarios for Block-VN;

3. *Experimental studies*: Several research articles propose blockchain-based solutions to address various security challenges in IoT and smart grid systems. Following on from their previous work [68], presenting a lightweight blockchain for use in the IoT with the elimination of proof-of-work and the concept of coins, in this article, Dorri et al. [65] present a blockchain-based smart home framework that supports confidentiality, integrity, and availability of communications while minimizing overheads. Sharma et al. [62] propose a secure distributed architecture for IoT (called DistBlockNet) using software-defined networking and blockchain to securely verify versions, validate, and download the latest flow rule table for IoT forwarding devices. Aitzhan and Svetinovic [61] implement a proof-of-concept for decentralized energy trading that enables anonymous negotiation of energy prices and secure transactions without trusted third parties. Li et al. [58] employ consortium blockchain technology to implement a secure energy trading system for P2P trading scenarios and propose a credit-based payment scheme to reduce transaction confirmation delays. Gai et al. [30] present a consortium blockchain-based approach to protect the privacy of energy trading users in the smart grid without restricting trading functions. These proposed solutions demonstrate the potential of blockchain technology to enable secure, decentralized transactions without the need for trusted intermediaries. These efforts provide important progress in the development of secure and trustworthy systems in these domains, which are critical for the success of future smart cities and industries.

3.5.5. Dual-Map Overlay Analysis

Our study utilizes a dual-map overlay technique [20] to analyze citation patterns at a disciplinary level in smart cities' AI–blockchain research. The technique groups over 10,000 journals (according to JCR) into regions that represent publications and citation activities at a domain-level, providing a comprehensive view of how the field references intellectual sources. The resulting map, displayed in Figure 16, shows clusters of citing (left side) and cited (right side) journals, with trajectories indicating the frequency and strength of interconnections between them (the parameter of snap to centroids set as radius > 500). Using this map, we identify patterns of how published articles in the field reference other intellectual sources. Our analysis reveals a single dominant citation path in the dataset, with citing region #1 (mathematics, systems, mathematical) citing primarily to cited regions #1 (systems, computing, computer), #12 (economics, economic, political), and #18 (history, philosophy, records). Despite the literature of citing region #1 being supported by literature from almost all of the cited regions, only one significant relationship is recognized, with a z-score of 5.833 and f-value of 1114. Overall, our study provides a valuable insight into the citation patterns of smart cities' AI–blockchain research, which can be useful for researchers and practitioners in the field.

Figure 16 shows the main red path in addition to three secondary paths. The first secondary path includes purple links between citing region #5 (physics, materials, chemistry) and cited region #1, while the second path consists of dark blue links between citing region #10 (economics, economic, political) and three cited regions: #1, #7 (psychology, education, health), and #12 (economics, economic, political). The third path comprises light blue links between citing region #6 (psychology, education, health) and two cited regions: #1 and #5 (health, nursing, medicine). These paths suggest that the research in AI–blockchain applications in smart cities has a multidisciplinary nature and involves domains such as economics, healthcare, and physics. However, they also reveal that the primary focus of both the source and destination journals is computer science.

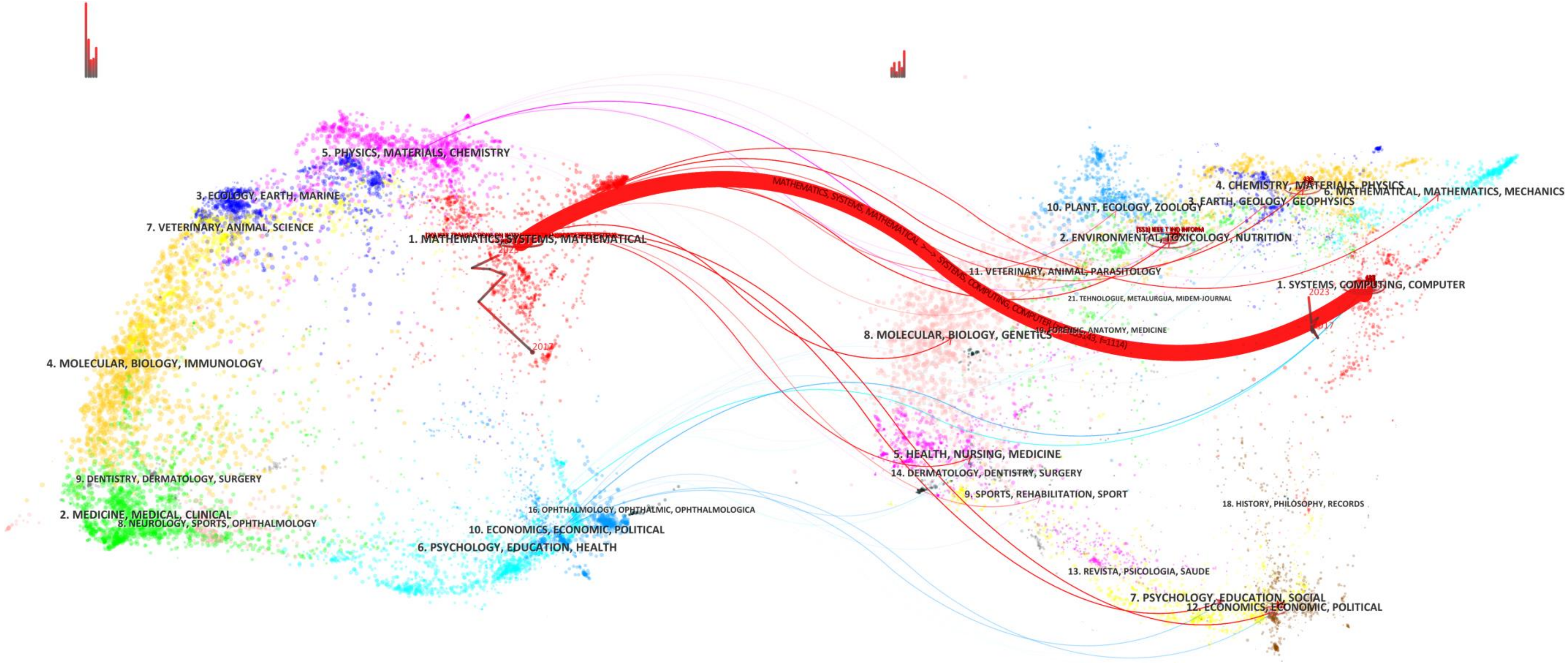

Figure 16. Domain-level citation pattern in the subject field.

4. Discussion

The integration of AI and blockchain has gained significant attention from both practitioners and academics [6]. In the context of smart cities, more stakeholders are recognizing the potential of this fusion to achieve sustainable development goals in urban digital ecosystems. Lotka's law analysis on our dataset shows a strong correlation between the number of authors and the number of publications. Bradford's law assessment identifies 13 core journals in this field. Our research results demonstrate the higher productivity of developing countries in this area. This could be attributed to the fact that smart city development is seen as an effective solution to alleviate the population pressure in developing countries and address their increasing demand for services and infrastructure [37].

This study identifies the social, conceptual, and intellectual perspectives of the field, revealing that authors lack strong collaborative relationships. Kumar N and Guizani M are in structural holes, while the most productive researchers are Tanwar S, Gupta R, and Kumar N, and King Saud University and Taif University are crucial institutions. Blockchain is the most interesting area for researchers to engage in co-authorship, and institutional collaboration focuses on urban planning. Federated learning is considered a future research hotspot, and combining blockchain and federated learning is a future trend, as previously mentioned by Hajizadeh et al. [6]. Nakamoto S, Sharma PK, and Ferrag MA are the top three highly cited authors, while Allam Z, Kim M, and Grieves M are the leading researchers in terms of centrality scores. The top three productive journals are *IEEE Access*, *IEEE Internet Things J*, and *IEEE Trans Ind Inform*, while the top three influential sources include the *Commun ACM*, *IEEE T Knowl Data En*, and *Appl Energ*. The trend in AI–blockchain integration has shifted toward encrypted IoT and urban planning, leading to new research fronts in this area. Overall, this study provides valuable insights into the current state and future directions of the field.

According to previous research by Hajizadeh et al. [6], potential future directions for AI–blockchain–IoT integration include: (i) collaborative machine learning models for secure and decentralized information sharing between intrusion detection system participants, (ii) collaborative attack mitigation models that utilize resources from other nodes to share the burden and mitigate attacks, and (iii) a trusted signature database that uses blockchain to create a trusted database of attack signatures, where a group of IoT nodes are connected to the blockchain [69]. Furthermore, Laouar et al. [70] and Yigitcanlar et al. [71] suggest that the digital transformation and sustainability of cities through the use of AI and blockchain technologies is the central topic of discussion in the urban planning and development community.

In Table 9, we present the completed body of knowledge proposed by Fitsilis and Kokkinaki [72] on the emerging research field of AI–blockchain convergence in smart cities. We use cluster titles extracted from various perspectives to describe the focus of the literature on specific areas of interest. This body of knowledge provides insights into the state of research in this field and serves as a guide for future studies. It highlights the essential attributes of AI–blockchain convergence in smart cities and emphasizes the close association between this convergence and the practical issues in smart cities practice. The practical applications of AI–blockchain convergence are evident in various domains, such as smart factories, smart agriculture, smart healthcare, smart grids, and electric vehicles, among others. We hope that this body of knowledge will be useful for researchers and practitioners in the field and inspire further research in this emerging area.

In Table 9, the areas of interest related to AI–blockchain convergence are spread across all components of the smart field, indicating that the literature is attempting to address all concerns related to this convergence. In addition to covering all blockchain-related issues and most AI methods and algorithms, the high proportion of technical terms in Table 9 demonstrates the significant role of IoT and 5G in facilitating AI–blockchain convergence for smart cities. The recent advancements in these two technologies, coupled with the need for suitable communication networks to support connected objects in smart cities, have made them indispensable components of this field. Researchers in this area must consider these technologies to build effective AI–blockchain solutions for smart cities. We hope that this table will aid researchers in gaining a comprehensive understanding of the scope of this field and provide a foundation for future research directions.

Table 9. Smart cities body of knowledge adapted from Fitsilis and Kokkinaki [72].

Component	Sub-Component	Area of Interest
Applied computing		blockchains; consortium blockchain; consensus mechanism; smart contract; data fusion; big data; information retrieval; computation offloading; peer-to-peer computing; volunteer computing;
Human-centered computing		5G/6G mobile communication; wireless sensor networks; vehicular ad hoc networks; encrypted IoT; data consumer; electronic mail; sensing efficiency; electric vehicles; vehicle to grid; microgrid
Social and professional topics	Computing/technology policy	privacy preservation; optimization; IoT security; sustainability
	Professional topics	natural gas; digital transformation; industry 4.0; agriculture 4.0; healthcare; biomedical monitoring; urban planning; energy market; energy transition; energy exchange; digital finance; energy internet
Computing methodologies		computational modeling; data models; predictive models; artificial intelligence; reinforcement learning; federated learning; deep learning; metaheuristics; anomaly detection
Information systems	Information systems applications	cyber physical system; intelligent transportation system; intrusion detection system; malicious application; servers
Software and its engineering	Software organization and properties	authentication; key agreement; quality of service; task analysis
	Contextual software domains	smart cities; smart factory; smart grids; smart buildings; smart healthcare system

Our work differs from that of other scholars (e.g., Singh et al. [8], Kiruthika and Ponnuswamy [2], and Gupta et al. [9]) in that we do not focus on one technology (e.g., IoT or 5G) as the foundation for the convergence of AI and blockchain. Instead, we analyze all relevant publications to identify other enablers and emerging trends in this field.

5. Conclusions

The growing number of publications on AI–blockchain integration in smart cities indicates increasing academic attention to this research area. However, few studies have conducted a systematic scientometric visualization of the literature in this area. The main objective of this study is to fill this gap by a bibliometric analysis of 505 papers published from 2017 to 2023 using co-authorship analysis, co-word analysis, and co-citation analysis. Our study provides descriptive statistics of each component of the bibliographic information and uncovers collaborative relationships, key concepts, research foci, leading scholars, influential sources, emerging trends, and primary milestones in the development and evolution of the subject area. We present this article as an overview of the convergence of AI and blockchain in smart cities to the academic community and practitioners in this field. Based on our results, we suggest several related topics for further research, which include federated learning, encrypted IoT, and urban planning. These topics are emerging trends identified by the bursting analysis.

Although we have made all efforts to increase the quality of our analysis, we recognize several limitations. First, our search was limited to publications listed on WoS. Second, the predominance of quantitative methods in bibliometric analysis makes the content or quality of publications uninterpretable [73]. This may have led to the inclusion of some publications in the analysis which in fact deal with a topic other than the convergence of AI and blockchain in smart cities. Finally, there may exist articles that do not contain the search term but are nevertheless focused on the topic, and vice versa.

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Appendix A

Table A1 provides information on the clusters detected in the study, including the number of authors assigned to each cluster, the homogeneity of clustering measured by silhouette values, the average year of publication by authors of that cluster, and a list of keywords identified by natural language processing algorithms, including LSI, MI, and LLR. These algorithms offer qualitative information on the research focus of each cluster. Silhouette values closer to 1 indicate higher precision in clustering [75]. LSI is a linear document indexing method that generates low-dimensional representations of terms based on word co-occurrence. Mutual information measures mutual dependence between terms. LLR, on the other hand, provides the ratio between the probability of observing a keyword in both the input and the background corpus, assuming equal and different probabilities [76] and is considered to have better results than other methods by many researchers (e.g., Niu et al. [77], Su et al. [78], and Zhang et al. [79]).

Table A1. Summary of the largest co-authorship clusters in the subject field.

Cluster ID	Size	Silhouette	Mean (year)	LSI	MI	LLR
0	27	0.958	2020	smart agriculture; blockchain technology; communication infrastructure	blockchain platforms (1.19) [a]; temperature measurement (1.19); hyperledger (1.19)	*authentication* (8.21, 0.005) [b]; federated learning (2.76, 0.1); smart agriculture (2.5, 0.5)
1	24	0.854	2021	*reinforcement learning*; privacy learning; energy systems	privacy learning (0.64); intelligent transportation (0.64); vehicular internet of things (0.64)	*reinforcement learning* (5.91, 0.05); privacy preservation (5.91, 0.05); intrusion detection system (5.91, 0.05)
2	22	0.965	2020	medical services; data models; biological system modeling	healthcare informatics (0.67); fault detection (0.67); fourth industrial revolution (0.67)	*blockchains* (5.79, 0.05); healthcare informatics (2.87, 0.1); fourth industrial revolution (2.87, 0.1)
3	19	0.988	2019	consortium blockchain; differential privacy; neighboring energy trading	*encrypted internet of things* (0.2); privacy protection (0.2); consortium blockchain (0.2)	*encrypted internet of things* (4.66, 0.05); consortium blockchain (4.66, 0.05); machine learning (4.66, 0.05)
9	8	0.985	2022	5g services; 5g internet; *5g networks*	5g internet of things (0.1); *5g networks* (0.1); 5g services (0.1)	*5g networks* (5.73, 0.05); 5g services (5.73, 0.05); machine learning (5.73, 0.05)

[a] (mutual information score); [b] (log-likelihood ratio, p-level).

Table A2 presents a comparison of the cluster names proposed by three algorithms (LSI, MI, and LLR) for the co-occurrence of keywords.

Table A2. Summary of the largest keywords' co-occurrence clusters in the subject field.

Cluster ID	Size	Silhouette	Mean (year)	LSI	MI	LLR
0	37	0.988	2020	medical services; *biomedical monitoring*; image edge detection	Internet of Medical Things (0.33) [a]; edge computing (0.33); automobiles (0.33)	*biomedical monitoring* (15.11, 0.001) [b]; image edge detection (10.06, 0.005); smart buildings (10.06, 0.005)
1	36	0.963	2020	*artificial intelligence*; cloud computing; edge computing	ev mobility (0.48); modern transportation system (0.48); power grids (0.48)	*artificial intelligence* (19.92, 0.000); cloud computing (16.1, 0.000); smart grids (11.43, 0.001)
2	35	0.925	2020	cloud computing; *smart factory*; manufacturing supply chain	digital manufacturing (0.1); edge analytics (0.1); production planning (0.1)	*smart factory* (13.96, 0.001); industry 4.0 (10.21, 0.005); precision agriculture (8.54, 0.005)
3	32	0.948	2021	*computational modeling*; differential privacy; mobile-edge computing	digital twins (0.28); aerial computing (0.28); intelligent reflecting surface (0.28)	*computational modeling* (13.35, 0.001); differential privacy (10.55, 0.005); autonomous systems (10.55, 0.005)
4	30	0.969	2020	*consortium blockchain*; commercial egg bank; membership fee	data trading (0.21); smart grid communication technologies (0.21); privacy protection (0.21)	*consortium blockchain* (17.39, 0.000); demand response (13, 0.001); machine learning (9.55, 0.005)
5	29	0.971	2021	*iot security*; iot applications; cybersecurity	cybernetics (0.11); cybersecurity lifecycle (0.11); cyber-physical security (0.11)	*iot security* (13.42, 0.001); internet of vehicles (13.42, 0.001); anomaly detection (8.02, 0.005)
6	27	0.983	2020	*electric vehicles*; smart grids; modern power system	automated services in microgrids (0.15); adaptive charging scheme (0.15); power generation (0.15)	*electric vehicles* (19.04, 0.000); power trading (12.67, 0.001); dematel method (8.94, 0.005)
7	26	0.985	2021	*computation offloading*; cloud computing; machine learning	energy finance (0.19); electric variables measurement (0.19); automation (0.19)	*computation offloading* (17.82, 0.000); resource management (16.38, 0.000); renewable energy (8.15, 0.005)
8	23	0.954	2019	*peer-to-peer computing*; urban sustainability; system analysis	blockchain defined networks (0.51); intelligence networking (0.51); descriptive systematic review (0.51)	*peer-to-peer computing* (12.78, 0.001); smart city (11.11, 0.001); smart contract (10.36, 0.005)
9	20	0.978	2020	heuristic algorithms; vehicle dynamics; logic gates	intelligent transportation (0.06); heuristic algorithms (0.06); logic gates (0.06)	*predictive models* (11.67, 0.001); energy prediction (11.67, 0.001); heuristic algorithms (7.69, 0.01)
10	20	0.956	2021	energy internet; to-peer computing; smart grids	internet (0.07); iov edge computing (0.07); instruction sets (0.07)	*energy transition* (15.04, 0.001); peer-to-peer energy trading (15.04, 0.001); energy internet (11.27, 0.001)
11	20	0.968	2020	*deep learning*; smart city; iot-oriented infrastructure	convolutional neural networks (0.2); point biserial correlation (0.2); identity (0.2)	*deep learning* (21.52, 0.000); smart city (17.63, 0.000); fog computing (14.31, 0.001)

Table A2. *Cont.*

Cluster ID	Size	Silhouette	Mean (year)	LSI	MI	LLR
12	19	0.950	2021	*digital transformation*; green revolution; fourth industrial revolution	private network (0.07); ecological shift (0.07); food fraud (0.07)	*digital transformation* (22.63, 0.000); smart agriculture (16, 0.000); ecological shift (7.5, 0.01)
13	18	0.950	2020	*consensus mechanism*; process models; smart communities	blockchain (0.04); bayes methods (0.03); decentralized consensus decision-making (0.03)	*consensus mechanism* (18.22, 0.000); bayes methods (9.05, 0.005); decentralized consensus decision-making (9.05, 0.005)
14	17	1.000	2021	smart cities; real-time systems; intelligent sensors	data integrity (0.53); integrity (0.53); network architecture (0.53)	*internet of things* (16.24, 0.000); edge computing (5.29, 0.05); network slicing (4.98, 0.05)
15	17	0.897	2021	*reinforcement learning*; recommender systems; data management	distributed ledger technology (0.06); federated learning (0.06); *reinforcement learning* (0.06)	*reinforcement learning* (25.92, 0.000); supply chain (15.34, 0.000); recommender systems (15.34, 0.000)
16	16	1.000	2020	*federated learning*; machine learning; network architectures	nonorthogonal multiple access (0.14); healthcare networks (0.14); medical imaging (0.14)	*federated learning* (24.05, 0.000); data privacy (13.27, 0.001); nonorthogonal multiple access (6.4, 0.05)
17	15	0.996	2020	optimization approach; energy negotiation; reinforcement learning	blockchain (0.04); stochastic processes (0.03); energy negotiation (0.03)	*optimization* (12.71, 0.001); stochastic processes (9.05, 0.005); energy negotiation (9.05, 0.005)
18	15	0.973	2020	deep learning; edge devices; occupancy detection	robotics (0.11); big data analysis (0.11); searching and indexing (0.11)	*data fusion* (13.42, 0.001); big data (10.32, 0.005); robotics (6.69, 0.01)
19	12	0.931	2020	*5g mobile communication*; artificial intelligence; 5g networks	queueing models (0.08); risk prediction (0.08); 5g networks (0.08)	*5g mobile communication* (12.35, 0.001); quality of service (12.35, 0.001); queueing models (7.19, 0.01)
20	11	0.964	2021	intrusion detection system; deep learning approaches; smart agriculture	*agriculture 4.0* (0.04); digital agriculture (0.04); deep learning approaches (0.04)	*agriculture 4.0* (8.37, 0.005); digital agriculture (8.37, 0.005); deep learning approaches (8.37, 0.005)

[a] (mutual information score); [b] (log-likelihood ratio, p-level).

Table A3 compares the topics proposed by three algorithms, LSI, MI, and LLR, for naming the clusters identified in the documents' co-citation network analysis.

Table A3. Summary of the largest documents' co-citation clusters in the subject field.

Cluster ID	Size	Silhouette	Mean (year)	LSI	MI	LLR
0	62	0.847	2017	cloud computing; edge computing; smart agriculture	fourth industrial revolution (1.03) [a]; research and development (1.03); gateways (1.03)	*smart grids* (6.65, 0.01) [b]; autonomous systems (6.21, 0.05); smart farming (6.21, 0.05)
1	41	0.925	2015	smart cities; data privacy; data models	*encrypted internet of things* (0.35); ipc key technology (0.35); blockchain defined networks (0.35)	*encrypted internet of things* (4.84, 0.05); ipc key technology (4.84, 0.05); blockchain defined networks (4.84, 0.05)

Table A3. *Cont.*

Cluster ID	Size	Silhouette	Mean (year)	LSI	MI	LLR
2	38	0.967	2019	*federated learning*; intelligent transportation systems; local differential privacy	intelligent transportation (0.47); resource allocation (0.47); deep reinforcement learning (0.47)	*federated learning* (11.95, 0.001); reinforcement learning (6.89, 0.01); computational modeling (6.36, 0.05)
3	38	0.902	2015	smart grids; artificial intelligence; telecommunication networks	urban sustainability (0.64); group signature (0.64); predictive analysis (0.64)	*consortium blockchain* (11.64, 0.001); demand response (7.75, 0.01); smart grids (6.67, 0.01)
4	27	0.972	2019	data privacy; *6g mobile communication*; long term evolution	beyond 5g (0.35); healthcare informatics (0.35); nonorthogonal multiple access (0.35)	*6g mobile communication* (9.67, 0.005); industry 5.0 (9.67, 0.005); blockchain (8.35, 0.005)
5	25	0.897	2017	edge computing; cloud computing; industrial internet	distributed databases (0.45); software-defined networking (0.45); deep reinforcement learning (0.45)	*computation offloading* (8.85, 0.005); recommender systems (8.85, 0.005); distributed databases (4.42, 0.05)
6	21	0.939	2019	deep learning; iot-oriented infrastructure; vehicular ad	Multi-access edge computing (0.12); artificial intelligence (0.12); video analytics (0.12)	*cyber physical systems* (13.05, 0.001); iot-oriented infrastructure (13.05, 0.001); smart city (9.31, 0.005)
7	21	0.946	2013	blockchain technology; smart agriculture; bibliometric analysis	wireless networks (0.2); temperature measurement (0.2); security and privacy (0.2)	*key agreement* (11.5, 0.001); authentication (9.47, 0.005); security (6.4, 0.05)
9	17	1	2018	smart cities; smart services; smart mobility	distributed storage (0.24); smart services (0.24); smart sensors (0.24)	*urban planning* (10.86, 0.001); e-governance (10.86, 0.001); iot (8.66, 0.005)
14	7	0.96	2011	artificial intelligence; cloud computing; edge computing	convolutional neural networks (0.22); health data (0.22); electronic health records (0.22)	*healthcare* (11.17, 0.001); convolutional neural networks (5.57, 0.05); decentralized governance (5.57, 0.05)
15	5	0.979	2019	smart meters; smart grids; energy management	blockchain (0.05); *volunteer computing* (0.04); drones (0.04)	*volunteer computing* (8.14, 0.005); drones (8.14, 0.005); routing (8.14, 0.005)

[a] (mutual information score); [b] (log-likelihood ratio, p-level).

Appendix B

TS = ((“artificial intelligence” OR “computer vision” OR ((image OR video OR document OR handwriting OR face OR pattern OR gesture OR semantic) NEAR/0 (understanding OR analys* OR sequence OR recognition)) OR (machine NEAR/0 (intelligence OR learning)) OR “visual search” OR “content-based retrieval” OR (Markov NEAR/0 (chain OR network)) OR “neural network” OR ((federated OR supervised OR unsupervised OR behavioral OR cognitive OR neural OR “game theor*” OR online OR reinforcement OR relational OR statistical OR distributed OR deep OR transfer OR Q OR edge) NEAR/0 learning) OR classification OR “adaptive control” OR “signal processing” OR clustering OR “data mining” OR “dimensionality reduction” OR ((choice OR graphical) NEAR/0 model) OR “independent component analysis” OR “inductive logic programming” OR ((kernel OR nonparametric OR spectral) NEAR/0 method) OR “Monte Carlo” OR “variational inference” OR “distributed reasoning” OR cognit* OR ontolog* OR “languages representation” OR “knowledge representation” OR “dynamic spectrum” OR chatbot OR “autonomous robot” OR “natural language processing” OR Bayesian OR “expert system” OR “support vector machine” OR “random forest” OR “decision tree” OR ((genetic OR learning) NEAR/0 algorithm)) AND (blockchain* OR "decentrali*ed autonomous organi*ation" OR (crypto NEAR/0 (currenc* OR asset)) OR "distributed ledger" OR "smart contract" OR "initial coin offering" OR "decentrali*ed ledger") AND (((smart OR intelligent) NEAR/0 (city OR cities OR sensing OR grid OR infrastructure OR transport* OR mobility OR logistics OR energy OR building OR home OR construction OR aquaculture OR food OR agriculture OR governance OR people OR econom* OR health* OR clinic* OR hospital* OR tourism OR living OR communit* OR factor* OR retail OR campus)) OR ((city OR urban) NEAR/0 (roadmap OR brain OR computing OR maturity)) OR "global cities" OR "global city" OR "citizen e-service"))

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